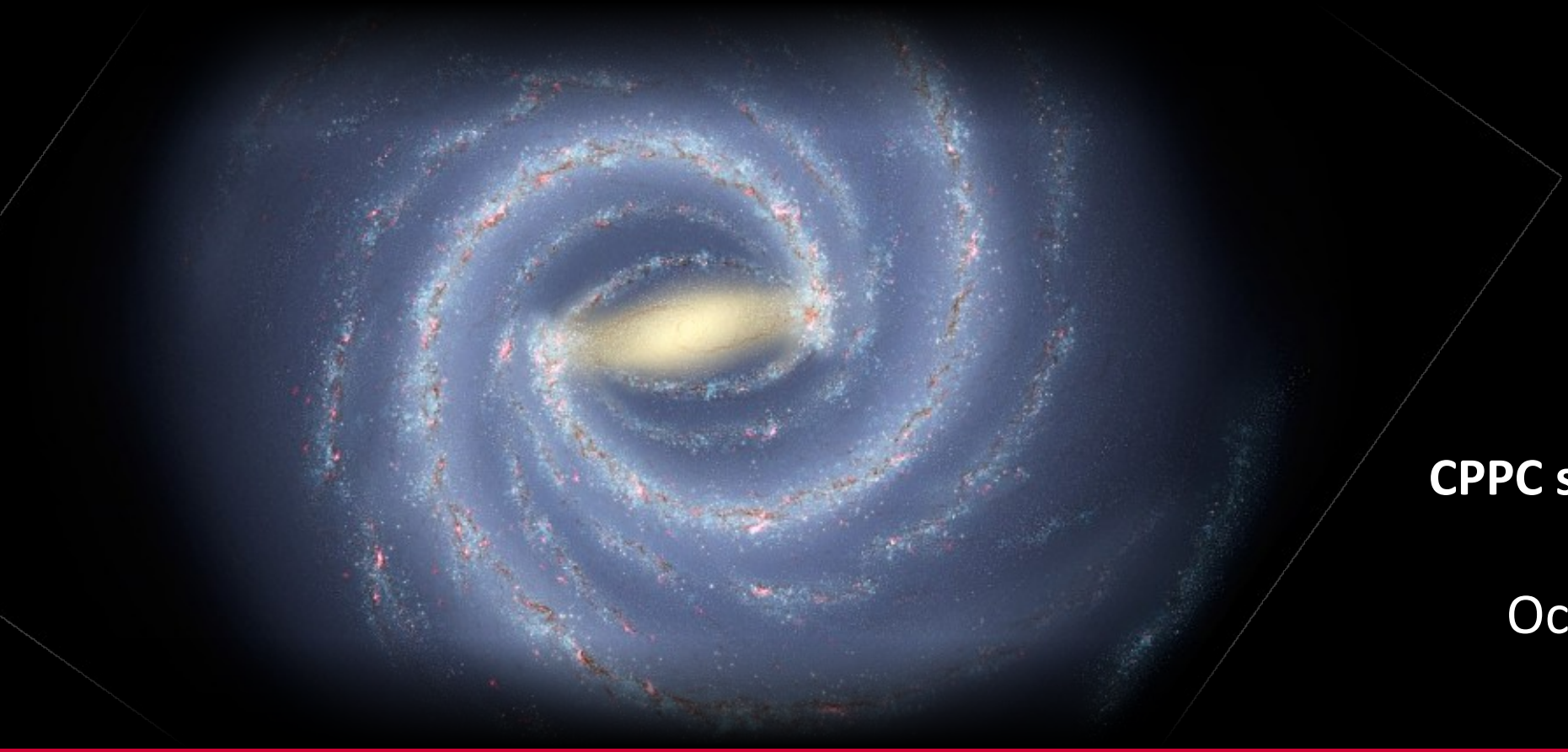
Physics-Informed Machine Learning for Dark Matter in Galaxies



CPPC seminar

Oct. 2026

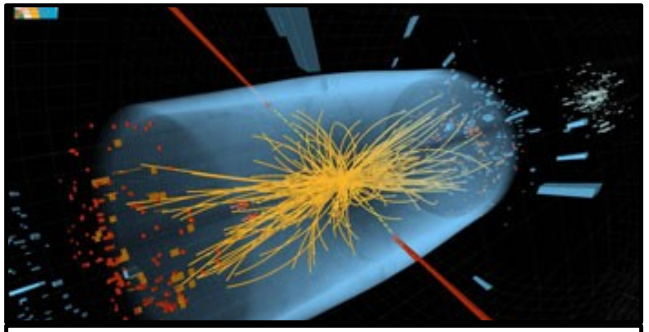
Sung Hak Lim

IBS CTPU-PTC

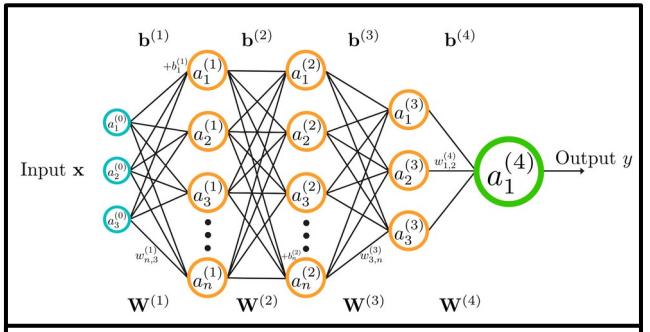
Institute for Basic Science

Research Interests

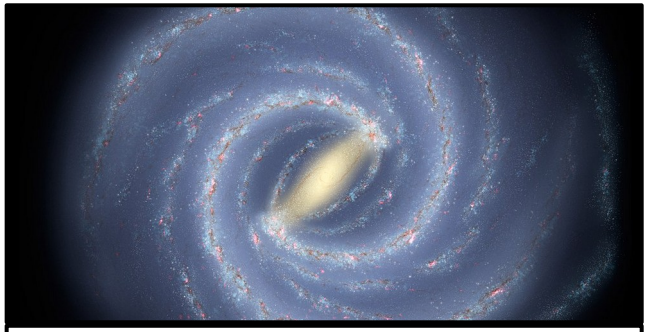
ML × Physics **— Data-Driven Studies on New Physics & Dark Matter**



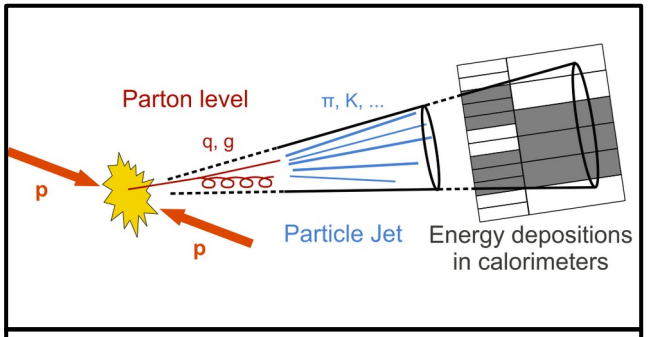
Collider Physics for BSM



Machine Learning



Astrophysics of Galaxies



Jet Physics and QCD



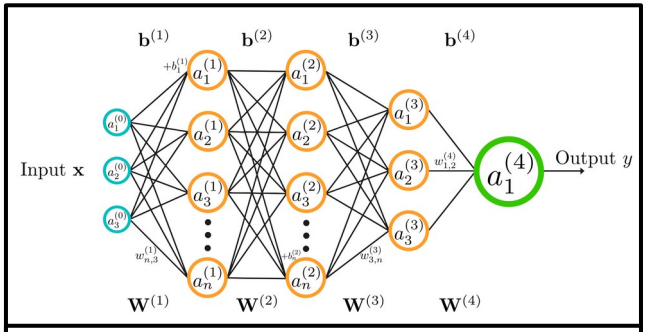
Dark Matter Physics

Data Physicist **— Connecting Data Science and Physics to Supercharge *Discovery***

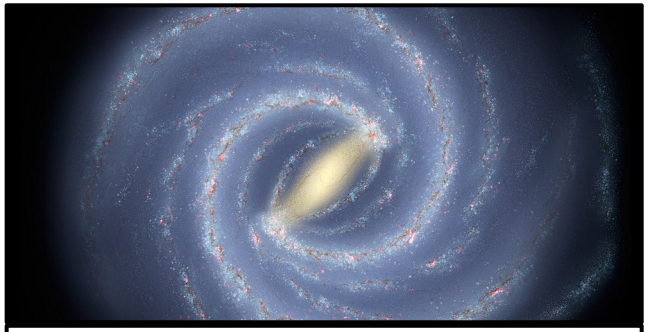
Research Interests

ML × Physics **— Data-Driven Studies on New Physics & Dark Matter**

Collider Physics for BSM



Machine Learning



Astrophysics of Galaxies

Astrophysics topic **—**
Machine Learning + Galaxies + Dark Matter



Jet Physics and QCD



Dark Matter Physics

Data Physicist **— Connecting Data Science and Physics to Supercharge *Discovery***

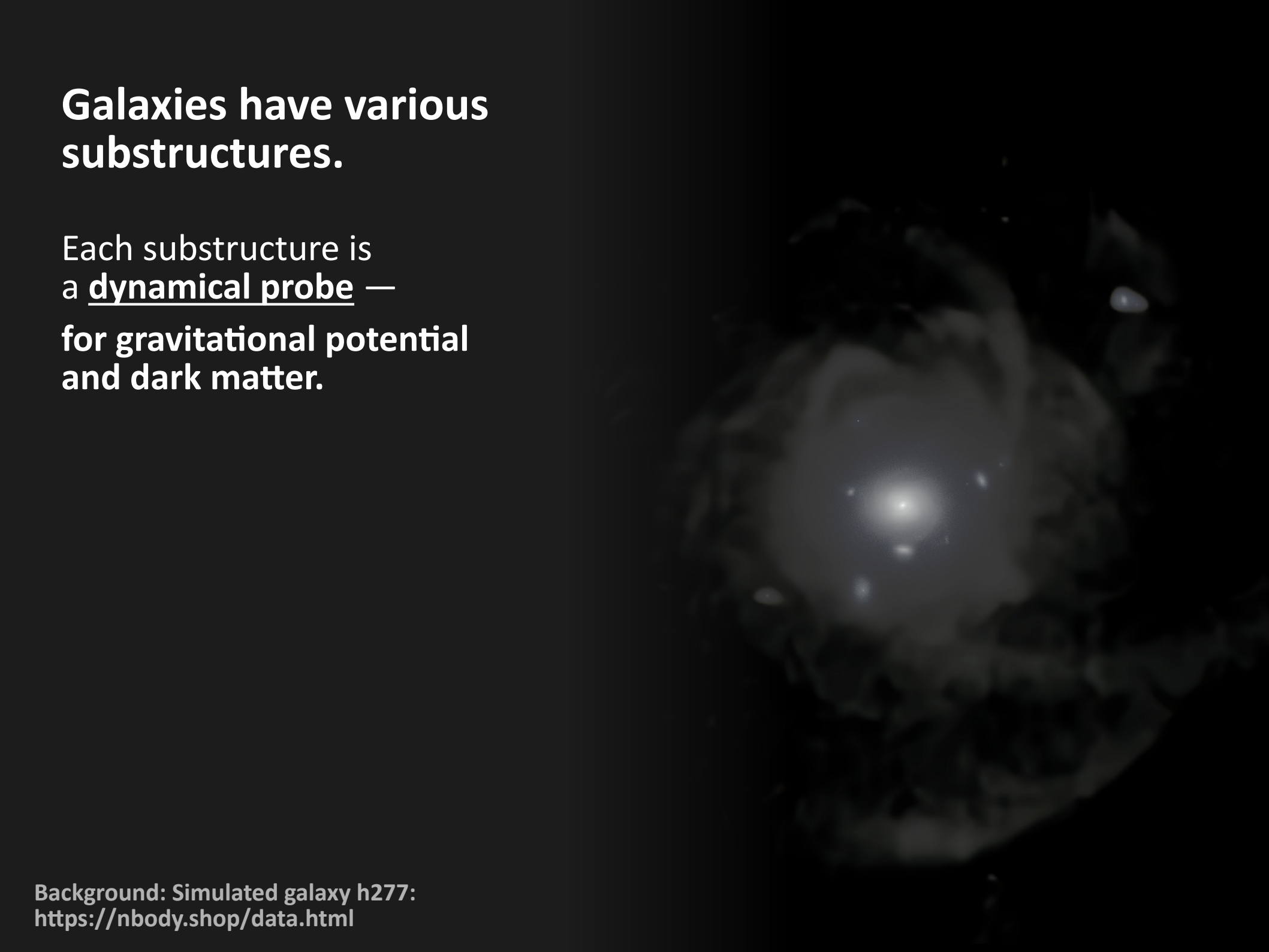


Formation of simulated Milky Way-like galaxy h277: https://nbody.shop/data.html

Galaxies have various substructures.

Each substructure is
a **dynamical probe** —

for gravitational potential and dark matter.



Background: Simulated galaxy h277:
https://nbody.shop/data.html

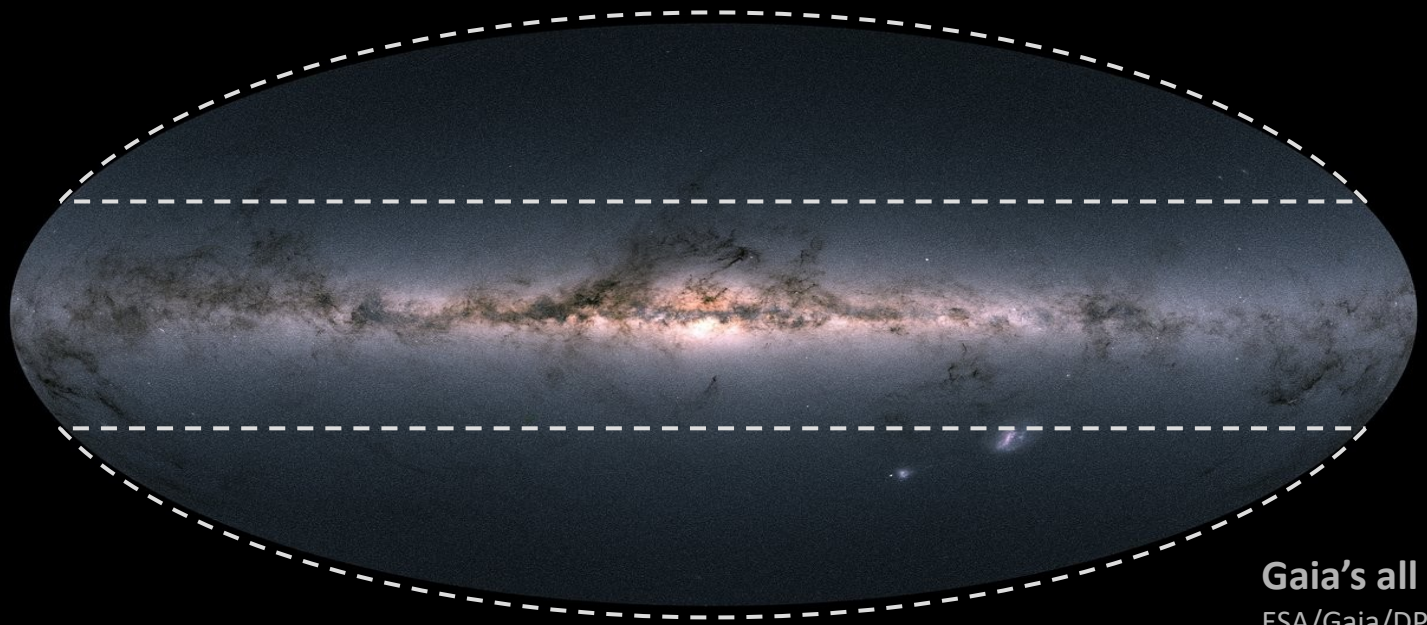
Stellar Halo

Around the solar system

Old stellar population in the MW.

Nearby stars from us
→ **precisely and completely measured**.

A good probe for
the local dark matter density in
the solar neighborhood.



Gaia's all sky view
ESA/Gaia/DPAC

Dwarf Galaxies

Faint, DM-dominated satellite galaxies with little baryonic activity.

→ cleanest probe of **DM halo shape** (cored vs. cuspy)

→ clean targets for indirect detection



Fornax Dwarf
Digitized Sky Survey 2



Ursa Minor Dwarf
Palomar Sky Survey



Draco Dwarf
Digitized Sky Survey

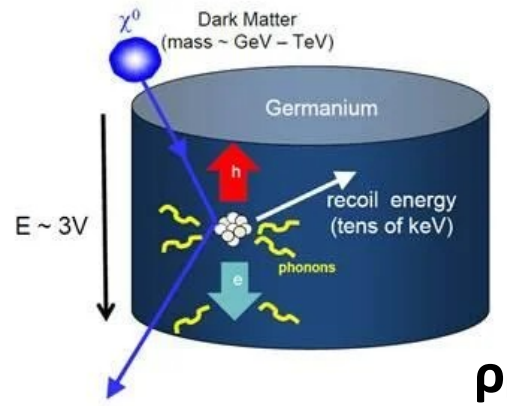
All these substructures encode

the gravitational potential
and the nature of dark matter.

For this talk, let us focus on

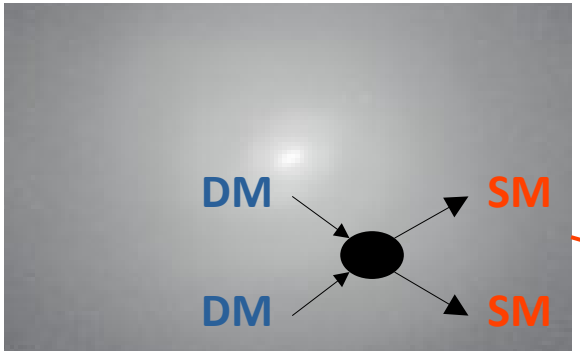
studies about **galactic dark matter**
by measuring **local dark matter density**.

Why measure local DM density?



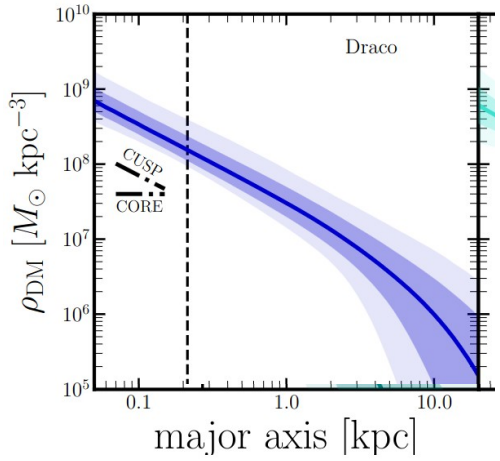
ρ_{DM} on earth?

Direct Detection of DM



ρ_{DM} at the source?

Indirect Detection of DM



Cored or Cuspy ρ_{DM}?

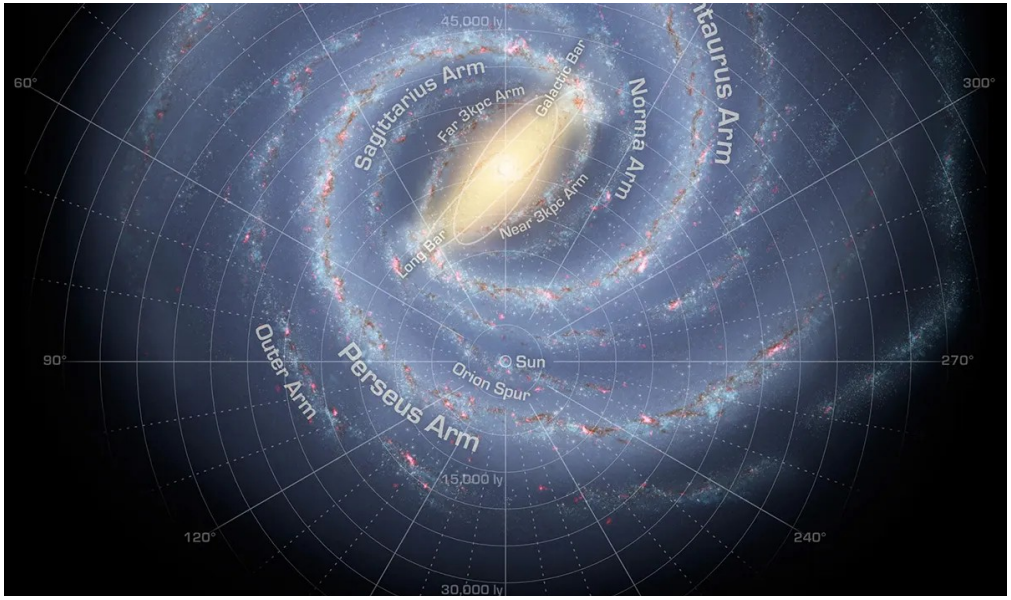
Understanding the Nature of Dark Matter

Local Dark Matter Density of the Milky Way

—

the key input for understanding dark matter physics!

How to measure local DM density?



Stars are moving under the gravitational potential of DM.

→

Galactic dynamics **provides insight on local DM density!**

Observable:
Stellar kinematics catalog

$$\{(x_i, v_i)\}$$

position and velocity of stars

?

Inference target:
Dark matter distribution

$$\rho_{DM}$$

Local dark matter density

Key Question **— How to estimate ρ_{DM} from stellar kinematics catalog?**

Framework: Collisionless Boltzmann Eq.

In the large-N limit, the phase space density *f(x,v)* of stars and *collisionless Boltzmann equation (CBE)* describes the dynamics.

$$\left[\frac{\partial}{\partial t} + \vec{v}\cdot\frac{\partial}{\partial \vec{x}} + \vec{a}\cdot\frac{\partial}{\partial \vec{v}}\right] f(\vec{x},\vec{v}) = 0$$

a(x) = $-\nabla\varphi$: gravitational acceleration field

Solving the CBE for a(x), then Poisson's equation gives *local dark matter density* model-independently.

$$\rho(\vec{x}) = -\frac{1}{4\pi G}\nabla\cdot\vec{a}(\vec{x})$$

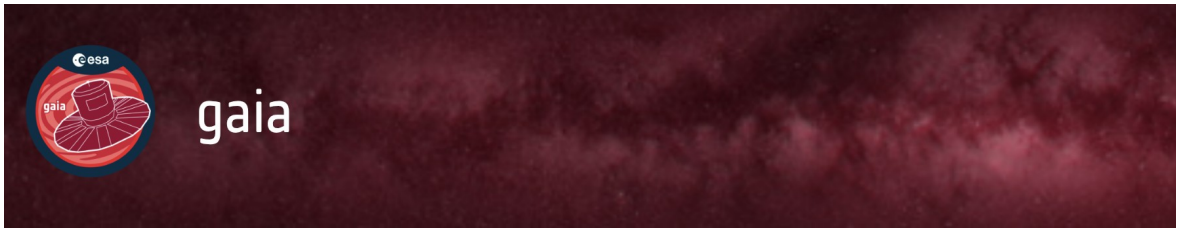
$\rho_{DM} = \rho - \rho_{baryon}$: local dark matter density

***Key idea* — If we can estimate *f(x,v)* from *data*, we can infer ρ_{DM}.**

Supercharging Inference Pipeline with ML

Stellar catalog

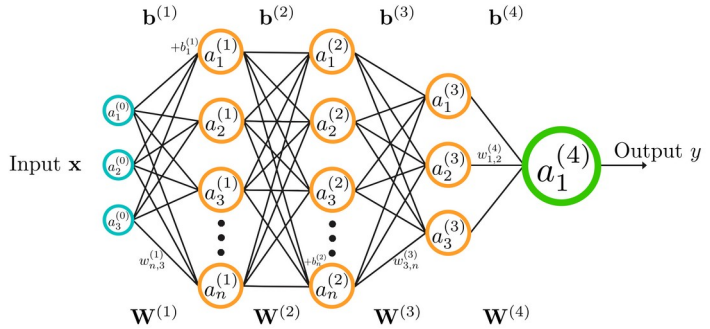
$\{(x_i, v_i)\}$



Phase-space density

f(x,v)

Neural Networks for Galaxy and Gravitational Field Modeling



Grav. Accel.

a(x)

Solve Poisson's equation

$$\rho(\vec{x}) = -\frac{1}{4\pi G}\nabla \cdot \vec{a}(\vec{x})$$

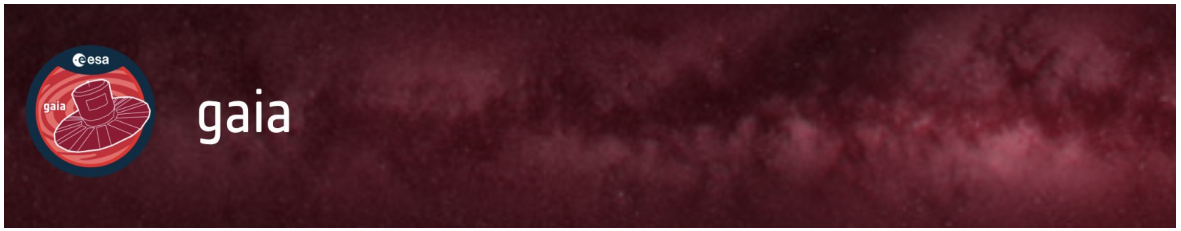
Mass density

$\rho(x)$, $\rho_{DM}(x)$

A Neural Estimator for Local Dark Matter Density

Stellar catalog

$\{(x_i, v_i)\}$



Phase-space density

$f(x,v)$

Normalizing Flows

Fit $f(x,v)$ by NN learning change of variables

Grav. Accel.

$a(x)$

Solve CBE (Physics-Informed Neural Network)

Model a(x) by NN minimizing CBE residual

Mass density

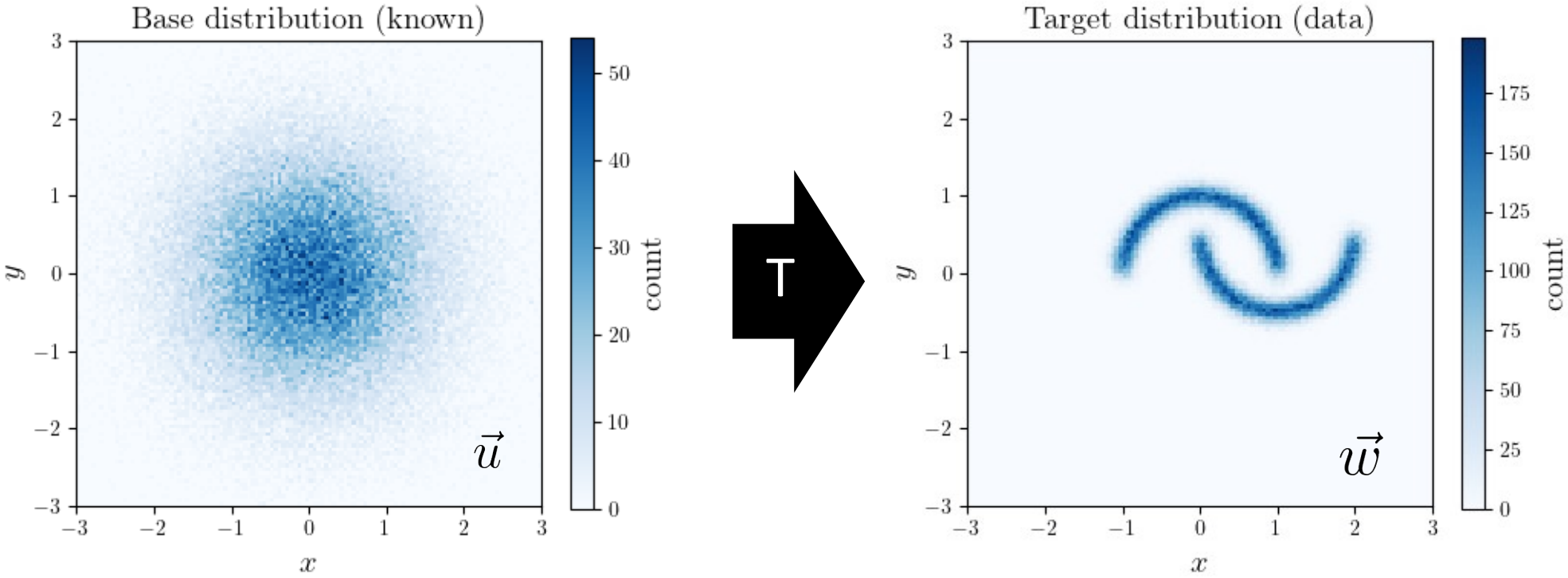
$\rho(x)$, $\rho_{DM}(x)$

Solve Poisson's equation

$$\rho(\vec{x}) = -\frac{1}{4\pi G}\nabla \cdot \vec{a}(\vec{x})$$

Normalizing Flows

Normalizing Flows (NFs) are an artificial neural network that learns a coordinate transformation of random variables.

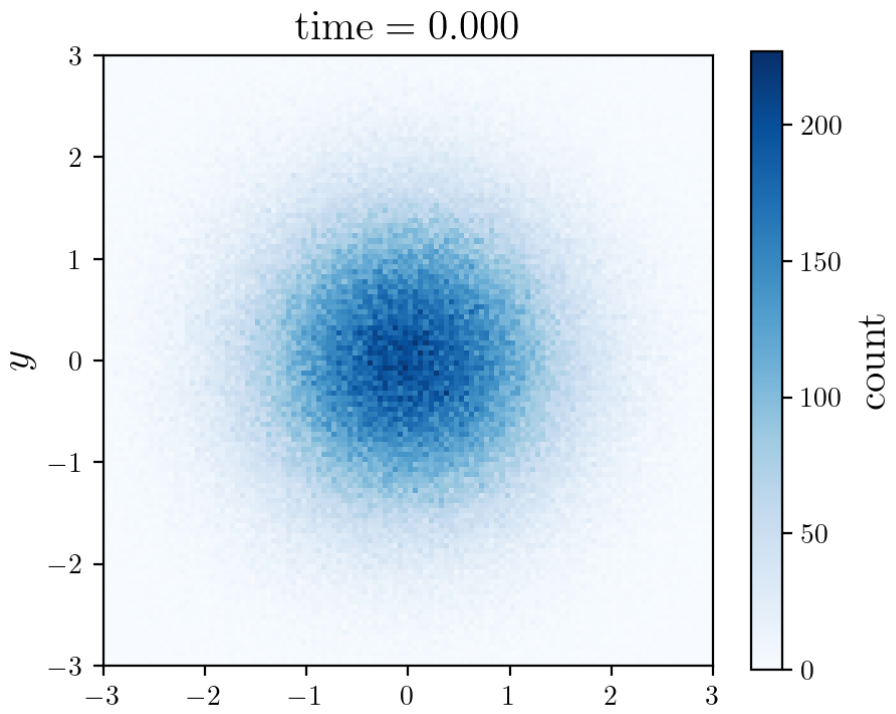


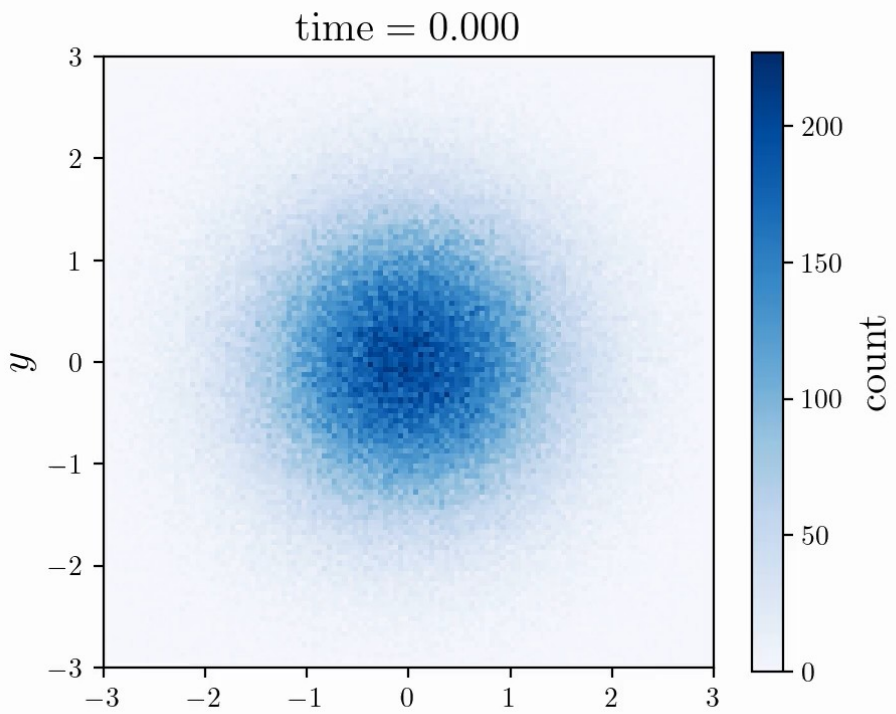
Main idea: if we can find a transformation mapping noise to data, we can use the transformation for the density estimation by change of variable formula.

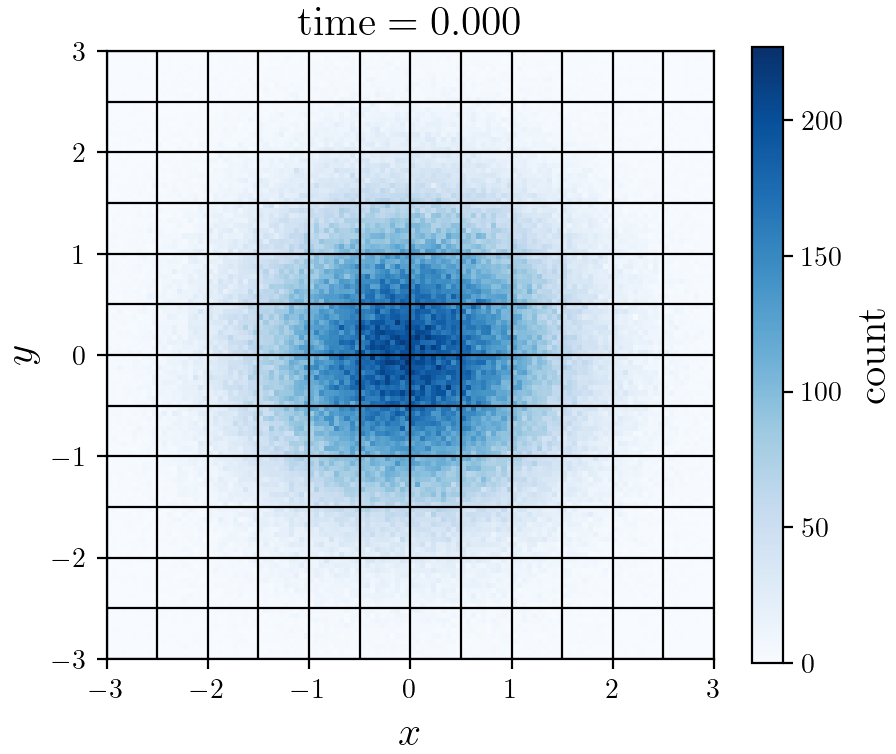
$$p_W(\vec{w}) = p_U(\vec{u}) \cdot \left| \frac{d\vec{u}}{d\vec{w}} \right|$$

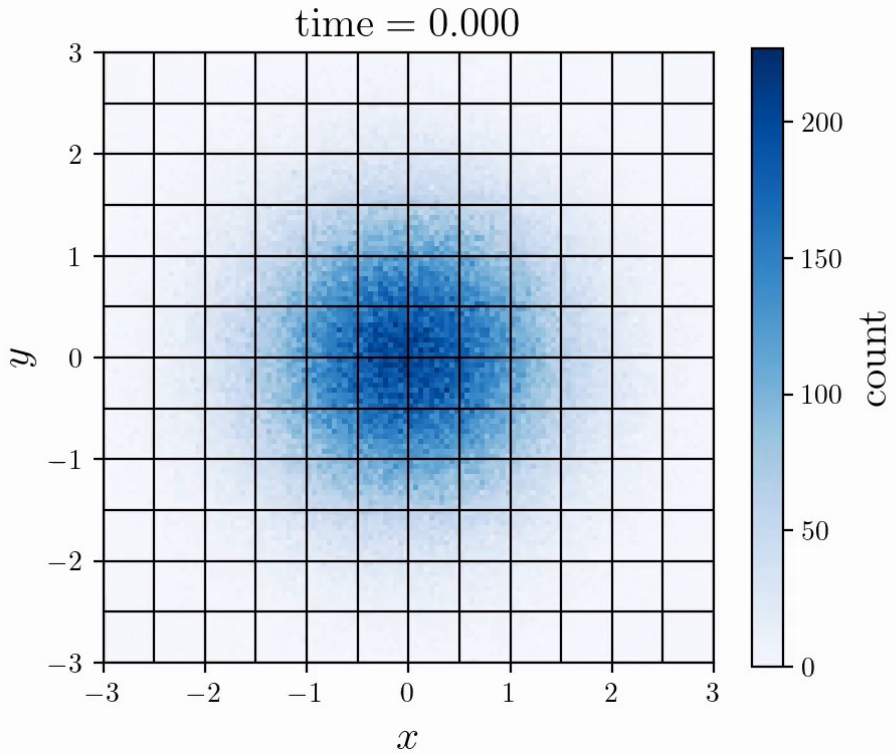
$$\vec{w} = T(\vec{u})$$

Neural Network


time = 0.000
y
count


time = 0.000
y
count


time = 0.000
y
x
count


time = 0.000
y
x
count

Acceleration Estimation with Physics-Informed Neural Network

PINN **is a neural network modeling solution of differential equations, simply minimizing the residuals.**

$$\left[\vec{v}\cdot\frac{\partial}{\partial\vec{x}}+\vec{a}\cdot\frac{\partial}{\partial\vec{v}}\right]f(\vec{x},\vec{v})=0$$

- Equilibrium CBE residual

How to solve?

NF **allows us to resample *v* at fixed *x*, so stacking CBE across multiple velocities gives an *overdetermined system* for *a*(*x*).**

$$\mathcal{L}(a(x))=\mathbf{E}_x\,\mathbf{E}_{v|x}\left[\vec{v}\cdot\frac{\partial f}{\partial\vec{x}}+\vec{a}\cdot\frac{\partial f}{\partial\vec{v}}\right]^2$$

Train a(x) by minimizing the CBE residual squared across data points.

Two Ways to Solve for a(x)

$$\mathcal{L}(a(x)) = \mathbf{E}_x \, \mathbf{E}_{v|x} \left[\vec{v} \cdot \frac{\partial f}{\partial \vec{x}} + \vec{a} \cdot \frac{\partial f}{\partial \vec{v}} \right]^2$$

Solve for the potential:

Green et. al. (arXiv: 2011.04673, 2205.02244)

Parametrize potential with a NN:

$$\Phi(x) = \mathrm{NN}(x;\theta)$$
$$a(x) = -\nabla\Phi(x)$$

✓ **Strictly conservative**
by construction

✗ **Training derivatives of NN**
may have minor quality issue

Solve for the acceleration:

An et. al. (arXiv: 2106.05981)
Naik et. al. (arXiv: 2112.07657)

Parametrize acceleration with a NN or directly solve

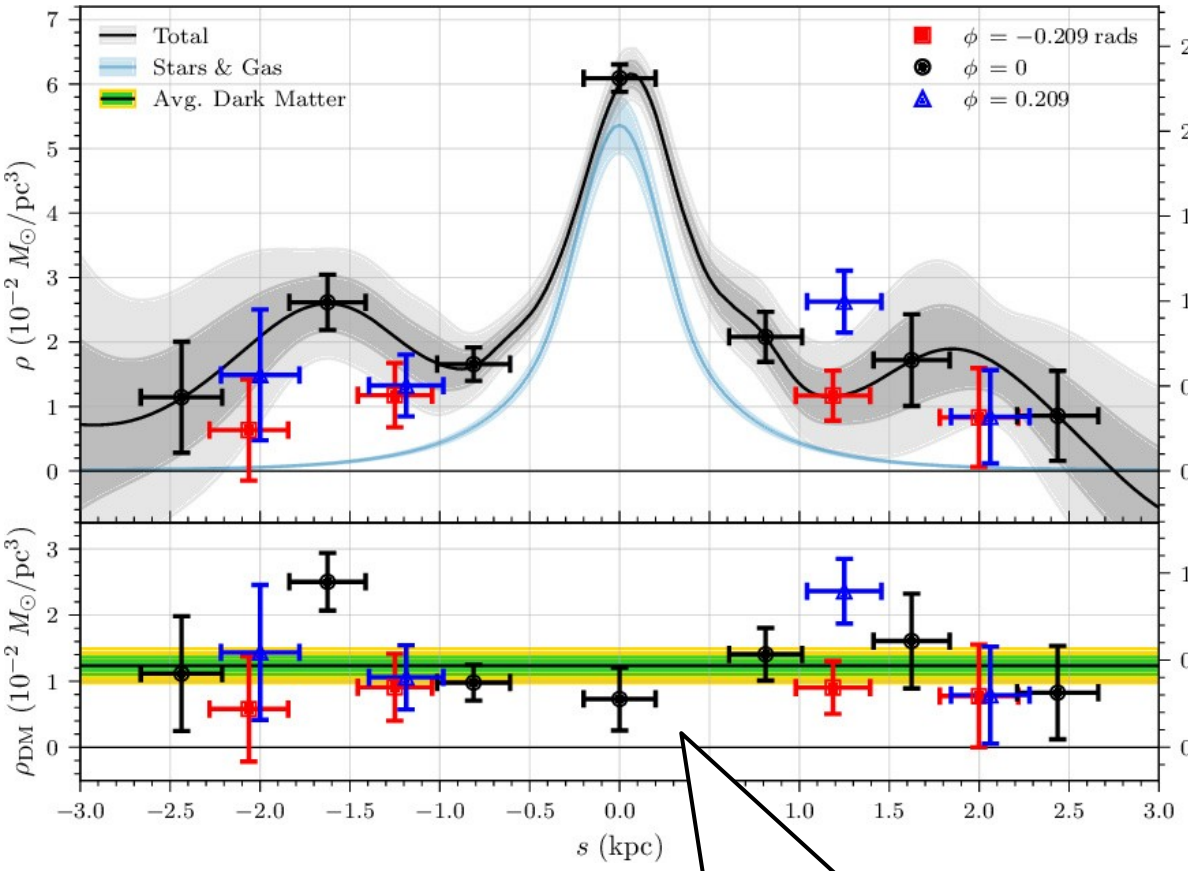
$$a(x) = \mathrm{NN}(x;\theta)$$

✓ **Analytic solution exists**
PINN training is optional

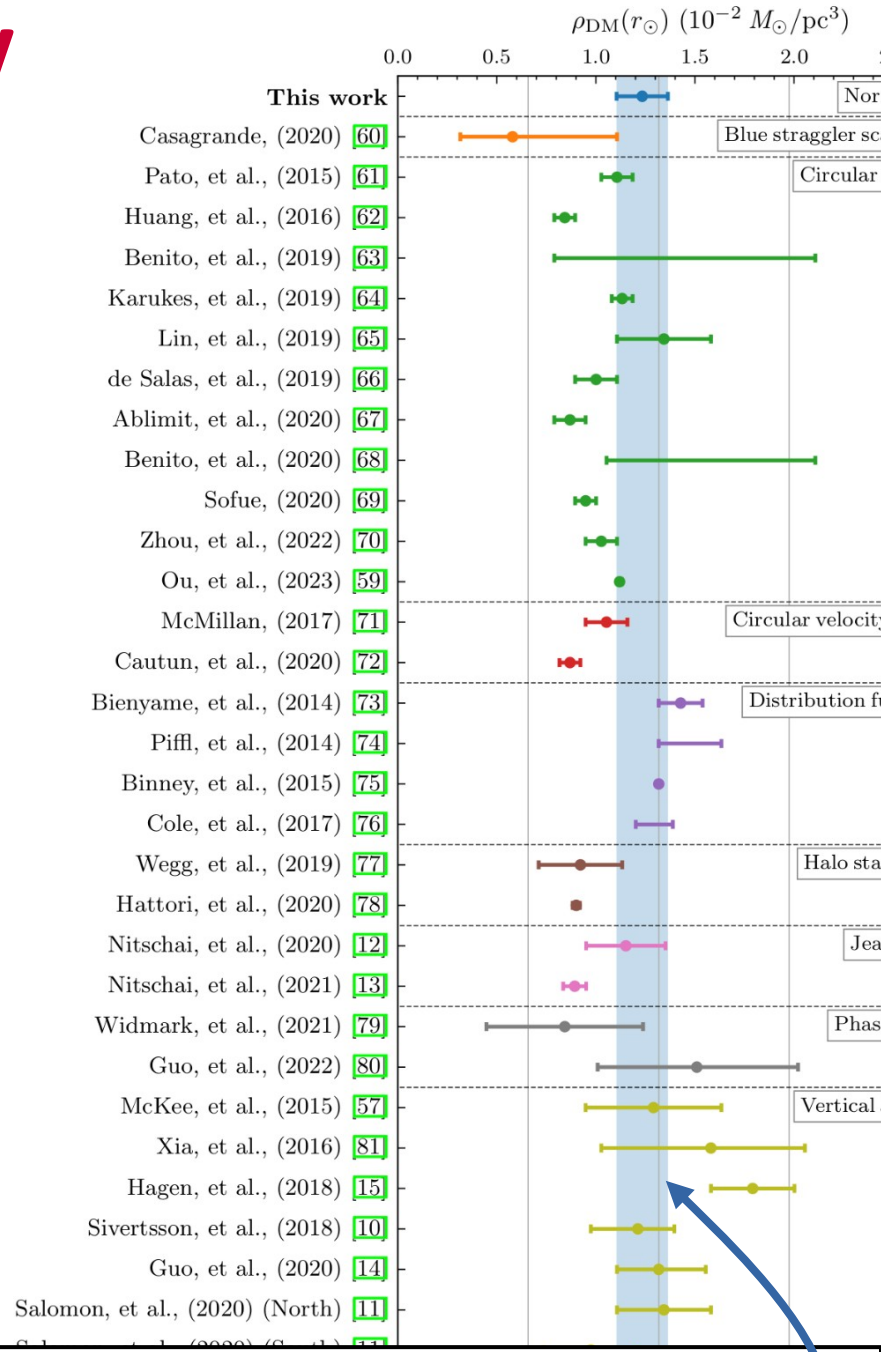
✗ **Not necessarily conservative**

Local Dark Matter Density of the Milky Way

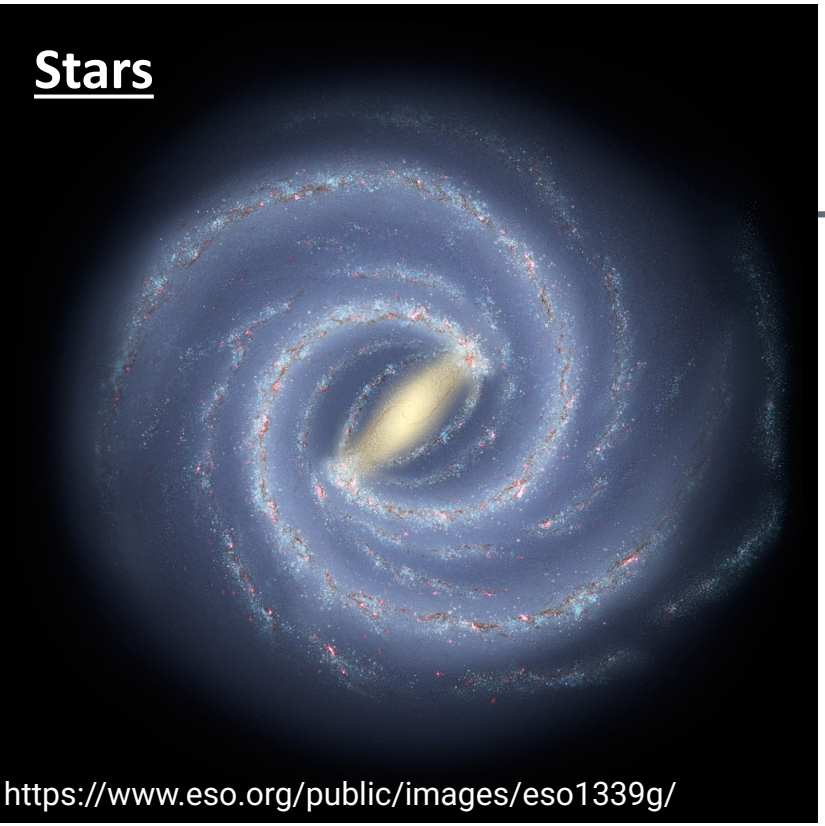
SHL et. al. (arXiv:2305.13358)

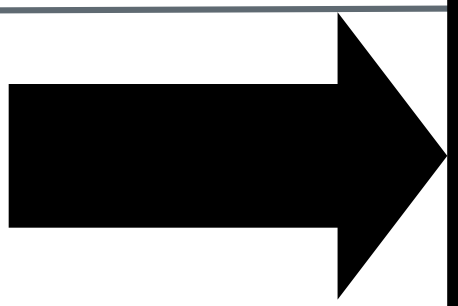


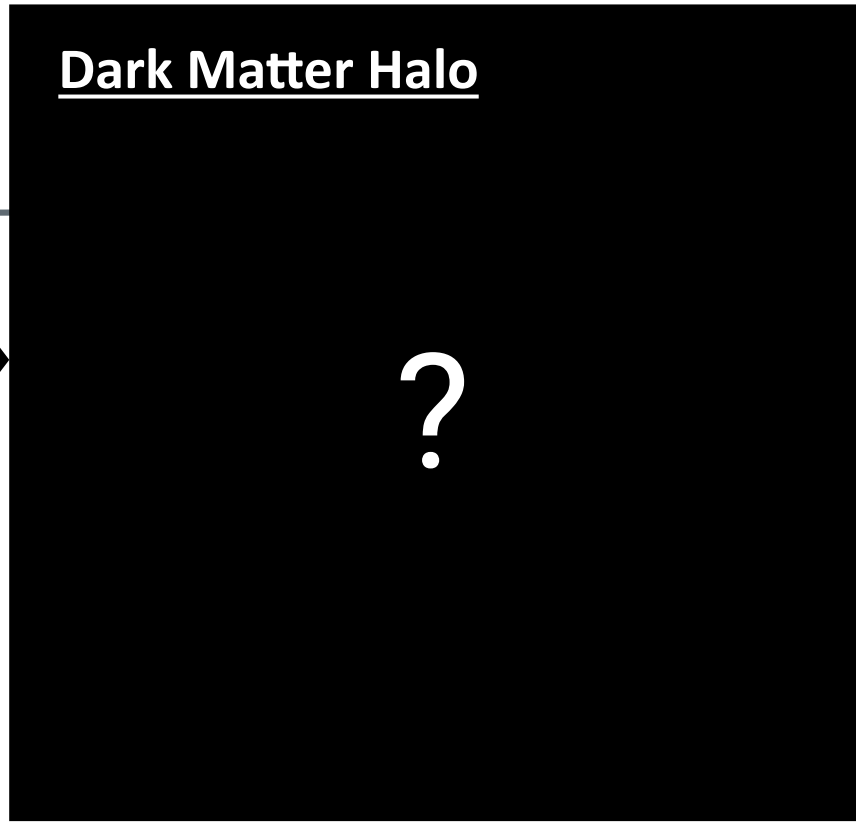
0.32±0.18 GeV/cm³



Taking the average of the DM mass density at the Solar radius, we find a local dark matter density: **0.47±0.05 GeV/cm³**

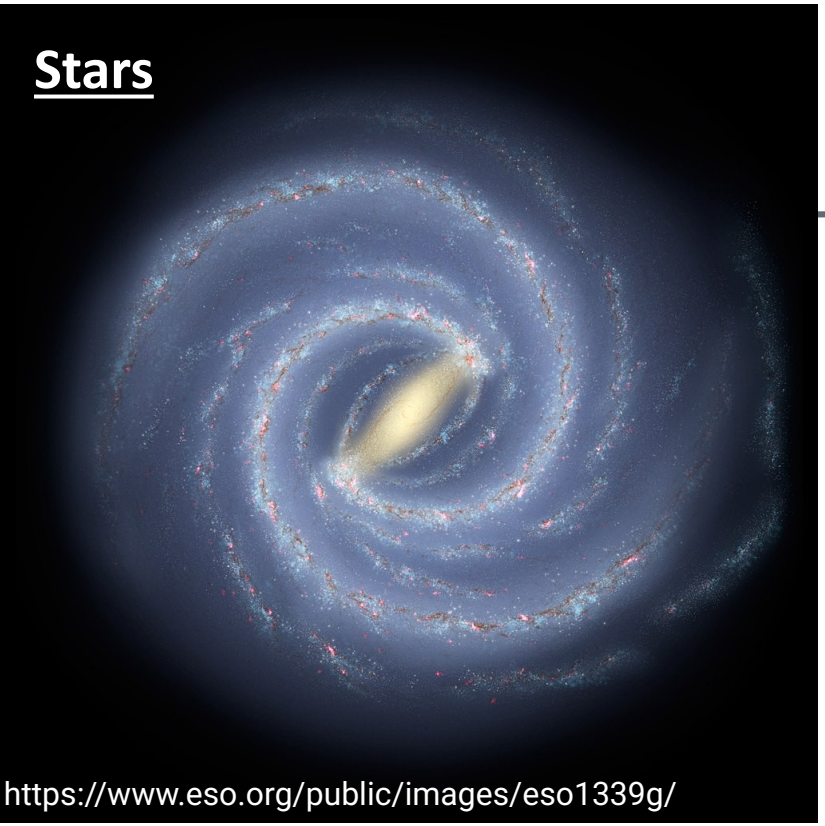


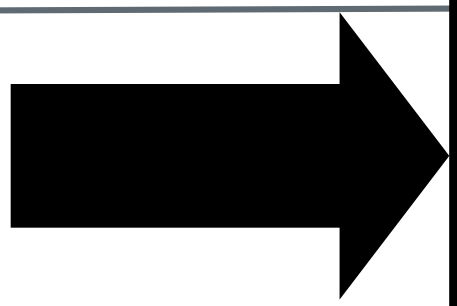


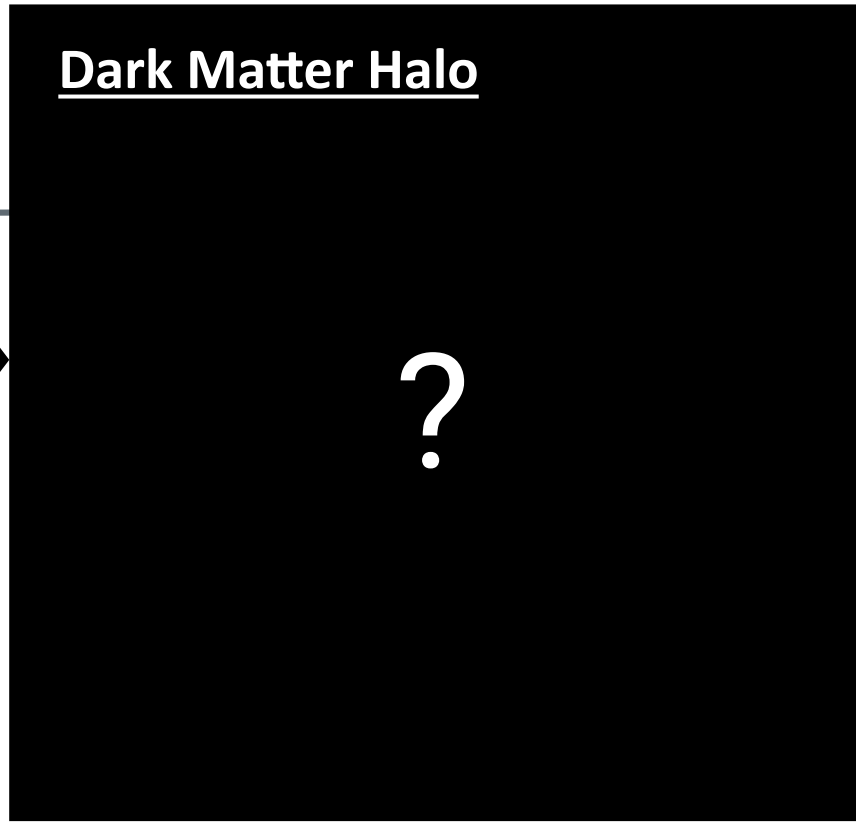


We have an unsupervised ML method to estimate **dark matter density** given **stellar distribution of a galaxy**.

THE END?

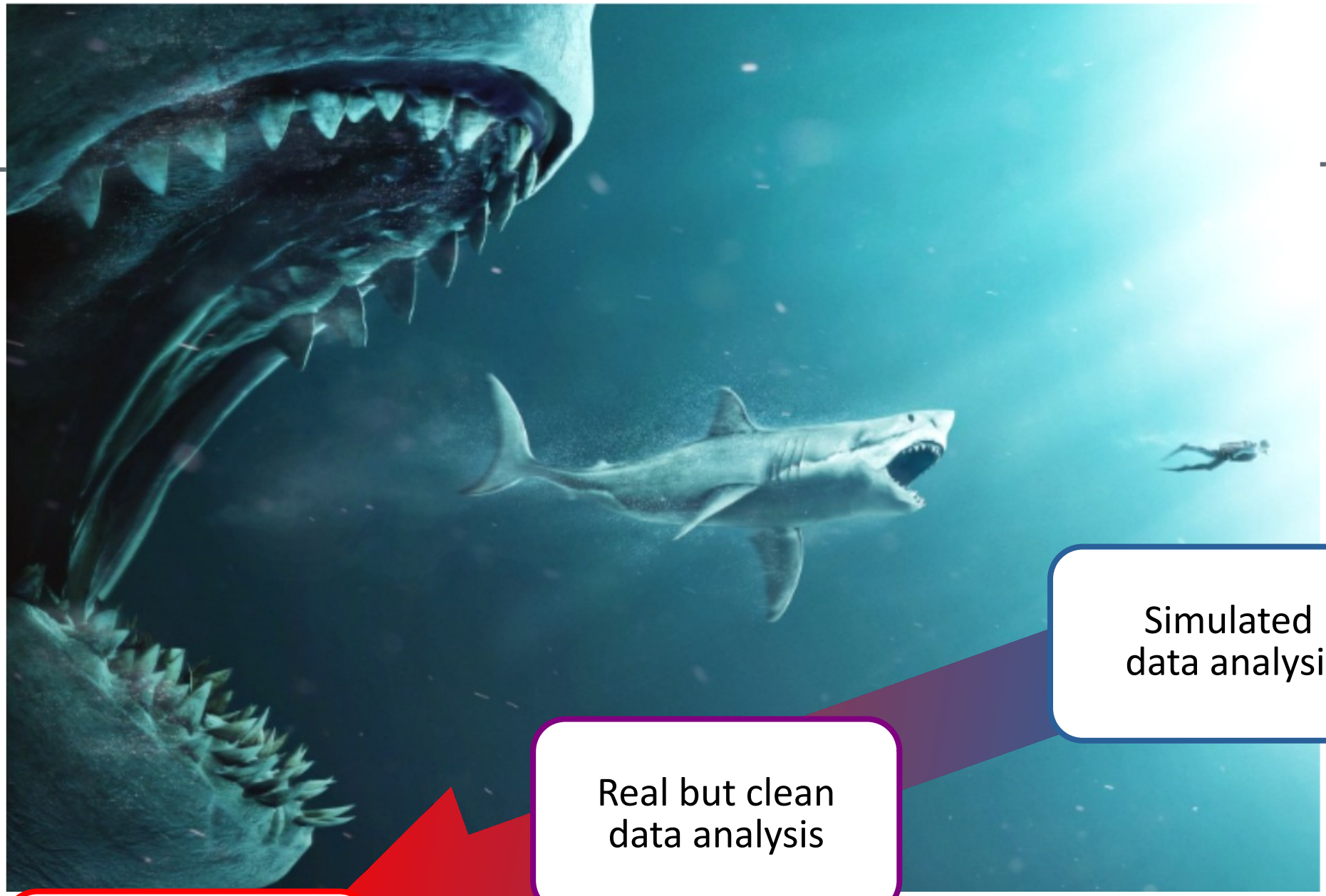






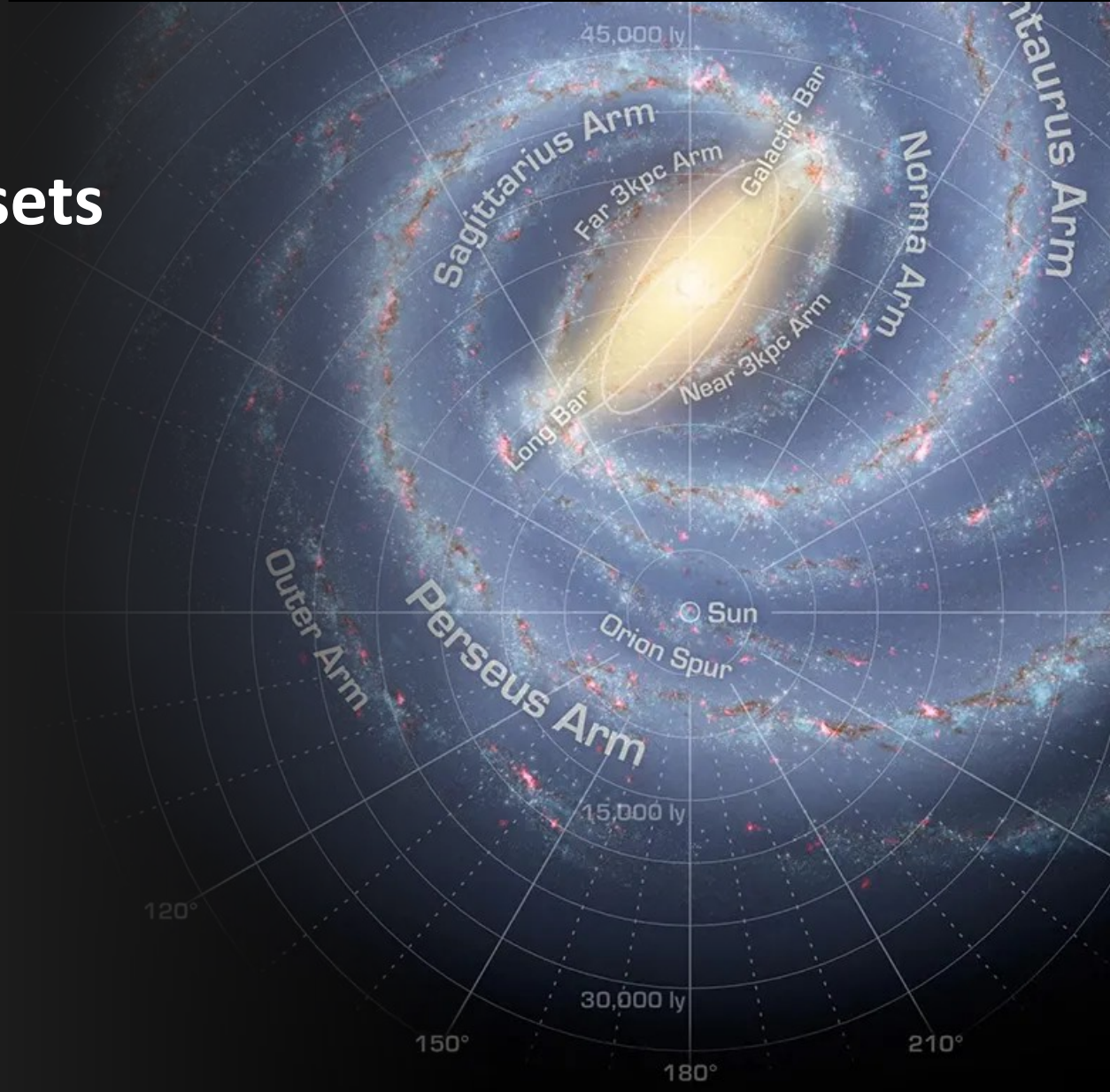
We have an unsupervised ML method to estimate **dark matter density** given **stellar distribution of a galaxy**.

THE END? → Of course not!


Simulated
data analysis
Real but clean
data analysis
Real, dirty
data analysis

Galactic Dynamics and Incomplete Datasets

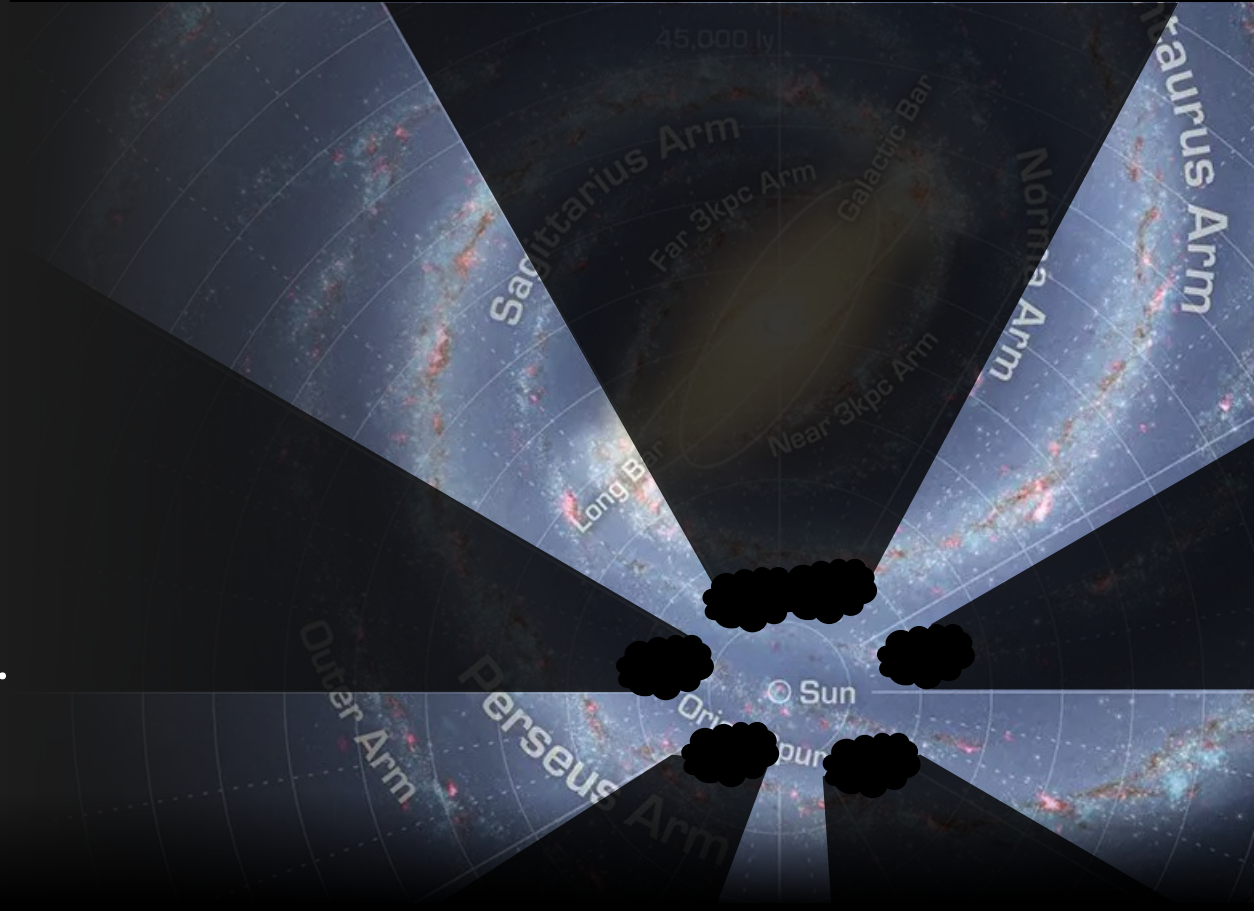
One of main challenges of applying this technique is that the dataset itself is **incomplete.**

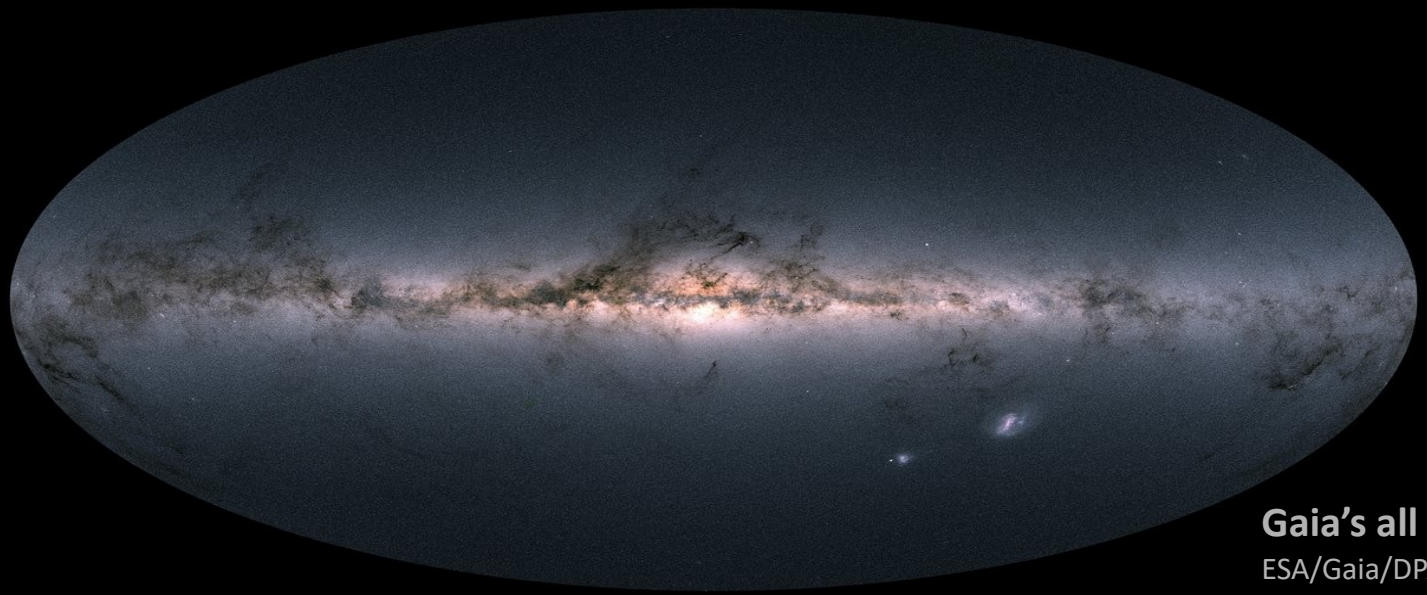


Dust Clouds

Interstellar dust clouds
obscure light
from stars behind them.

→ Obscured stars are
missing in Gaia catalog.





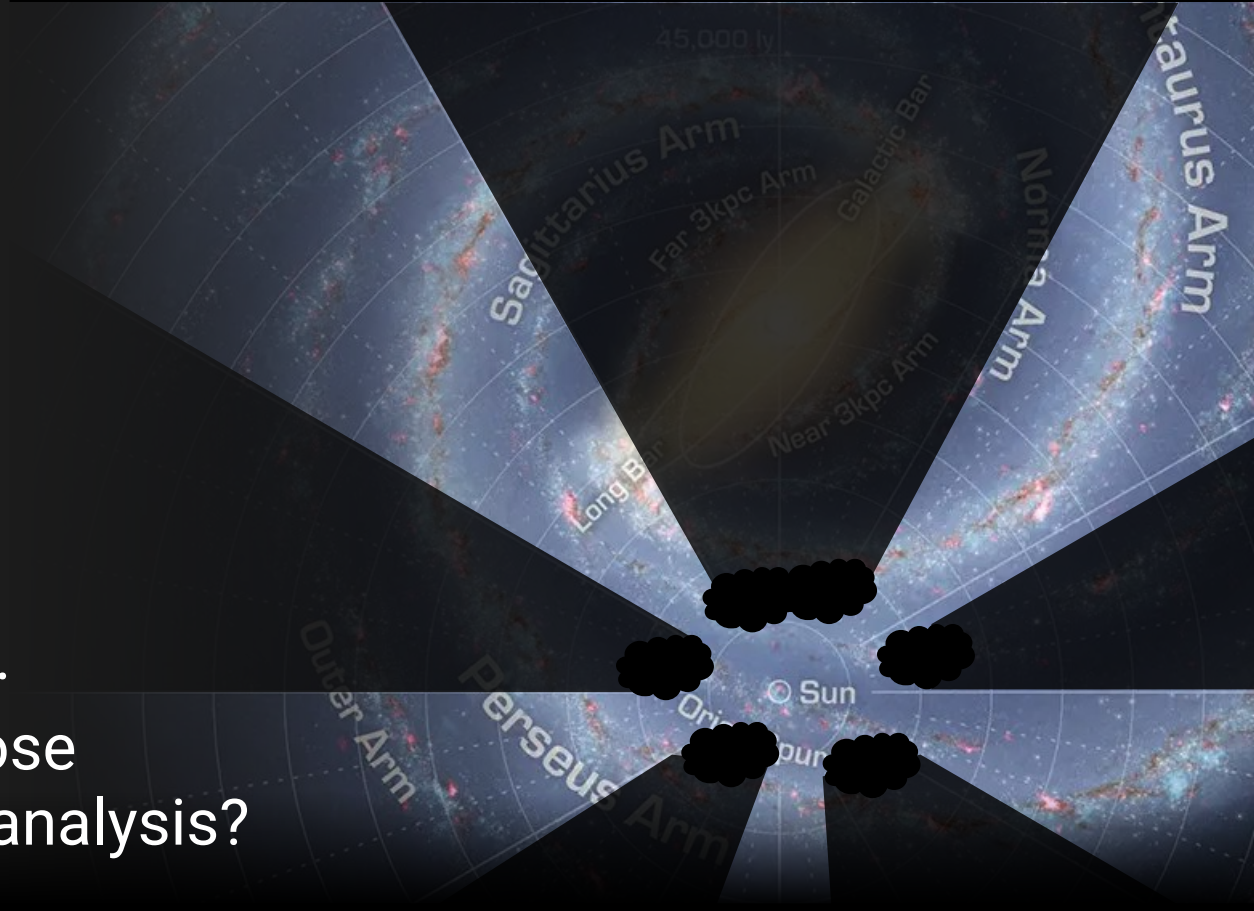
Gaia's all sky view
ESA/Gaia/DPAC

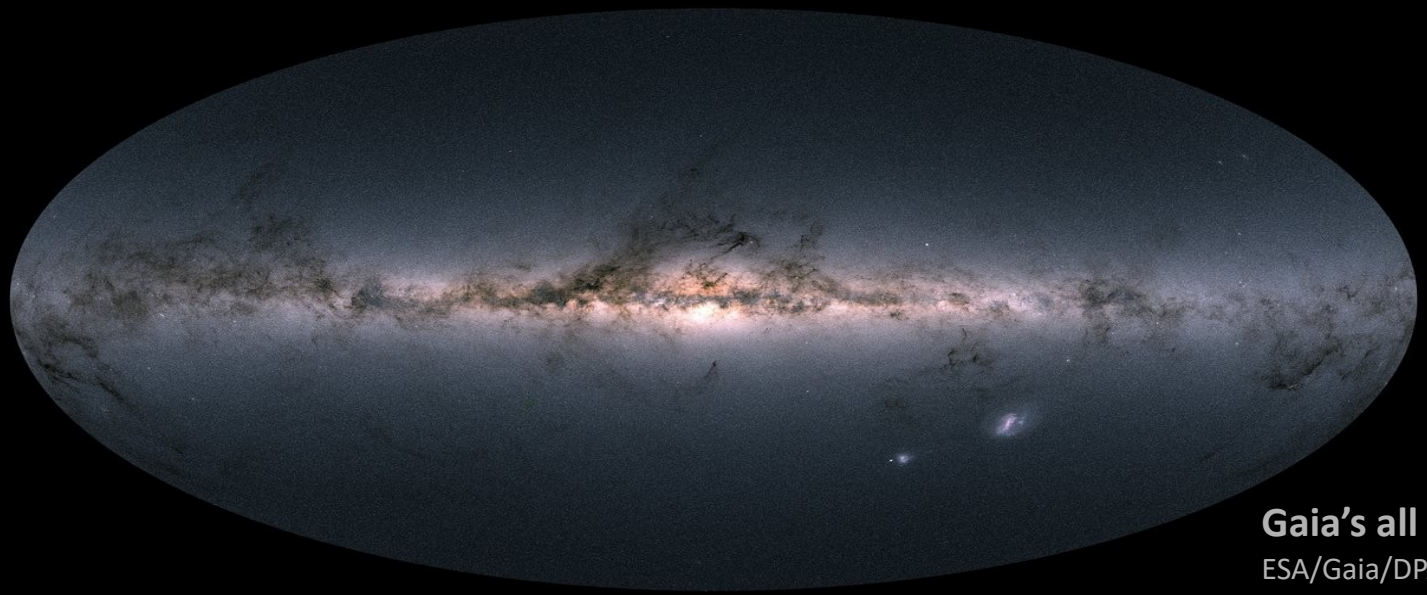
Dust Clouds

Interstellar dust clouds
obscure light
from stars behind them.

→ Obscured stars are
missing in Gaia catalog.

→ How can we **recover** those
for full 6D phase-space analysis?





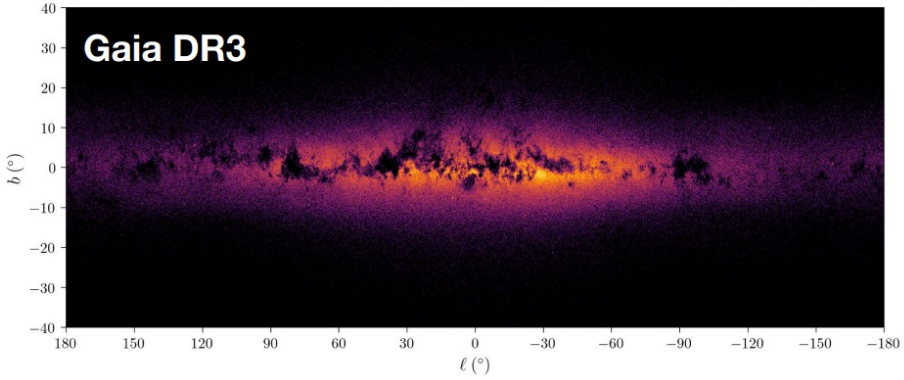
Gaia's all sky view
ESA/Gaia/DPAC

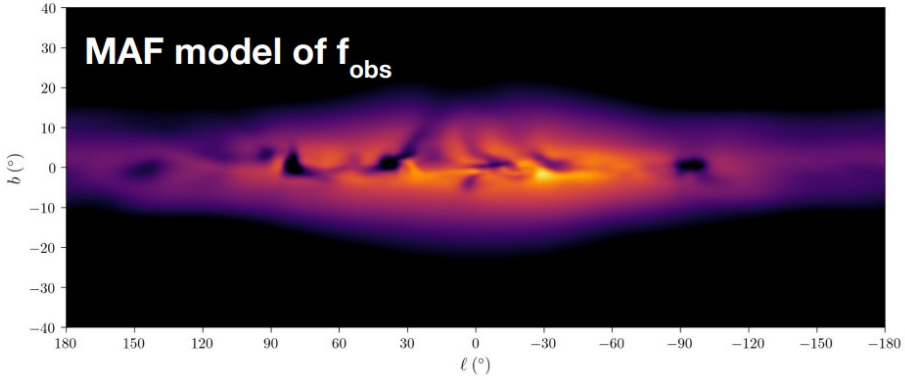


Sweeping the Dust Away -- Correcting the Phase Space Density of the Milky Way with Unsupervised Machine Learning

Eric Putney, David Shih, **SHL**, Matthew R. Buckley (arXiv:2412.14236)

PINN for Removing Dust Clouds

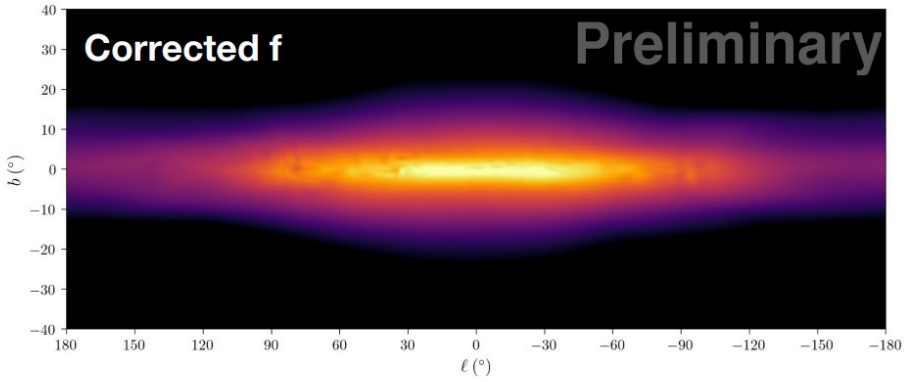




$$\frac{\partial f}{\partial t} = 0$$

Key Idea —

Equilibrium assumption can be utilized for inferring selection efficiency without referring dust map.



PINN-based Selection Efficiency Modeling

$$f_{\rm obs}(\vec{x},\vec{v}) = f_{\rm true}(\vec{x},\vec{v}) \times \epsilon(\vec{x})$$

NF model (observed PS, learned) **Selection efficiency** (dust, …)

↓ Apply CBE to log $f_{\rm true}$

$$\left[\vec{v}\cdot\frac{\partial}{\partial\vec{x}} + \vec{a}\cdot\frac{\partial}{\partial\vec{v}}\right]\log f_{\rm obs}(\vec{x},\vec{v}) - \vec{v}\cdot\frac{\partial}{\partial\vec{x}}\log\epsilon(\vec{x}) = 0$$

Acceleration model **Two unknowns**: a(x), ∇ log ϵ(x)

↓ Linear in unknowns — solvable by MSE minimization

$$\mathcal{L}(\phi,\log\epsilon) = \mathrm{E}_{\vec{x},\vec{v}}\left|\left[\vec{v}\cdot\frac{\partial}{\partial\vec{x}} + \vec{a}\cdot\frac{\partial}{\partial\vec{v}}\right]\log f_{\rm obs}(\vec{x},\vec{v}) - \vec{v}\cdot\frac{\partial}{\partial\vec{x}}\log\epsilon(\vec{x})\right|^2$$

PINN loss for *selection efficiency* — no dust map required.

Dust-Corrected Local Dark Matter Density

Normalizing Flows (NFs):

fits *f(x,v)* by learning change of variables

$$\vec{w}_{\text{data}} = \text{NN}(\vec{u}), \quad \vec{u} \sim \mathcal{N}(0, I)$$

$$f(\vec{w}) = p_U(\vec{u}) \cdot \left| \frac{d\vec{u}}{d\vec{w}} \right|$$

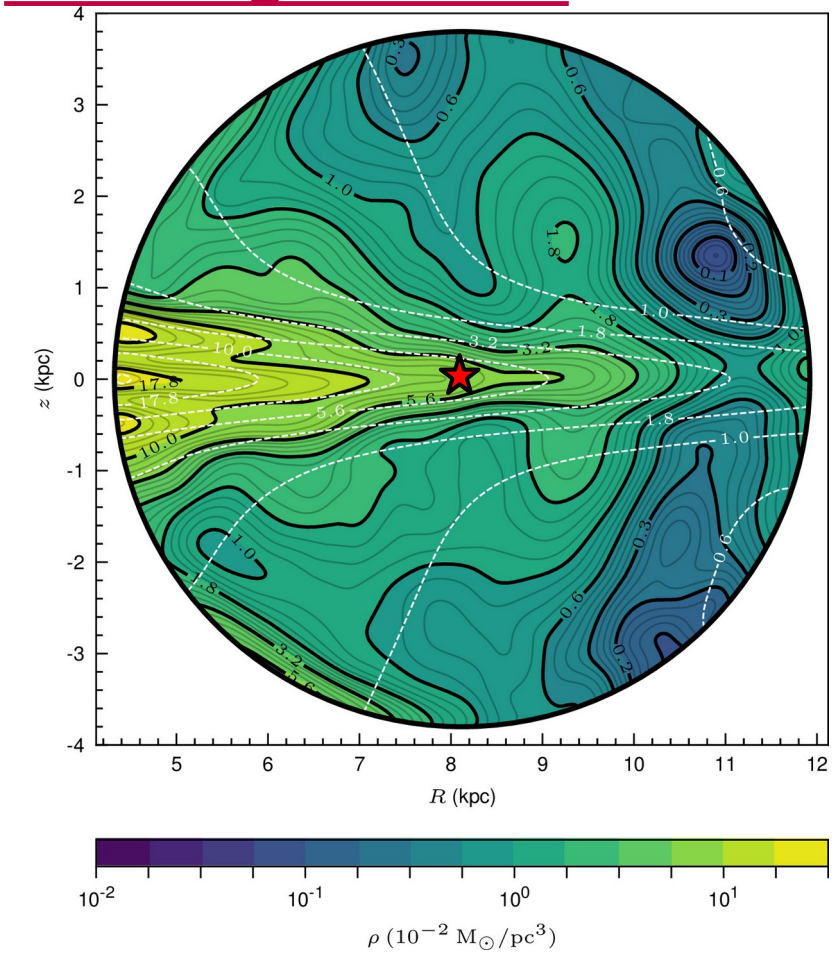
Physics-Informed NN (PINN):

solves *CBE* by minimizing residuals

$$\mathcal{L} = \mathbf{E}\left[\left| \vec{v} \cdot \frac{\partial f}{\partial \vec{x}} + \vec{a} \cdot \frac{\partial f}{\partial \vec{v}} \right|^2 \right]$$

Results of ρ_{DM} in solar neighborhood

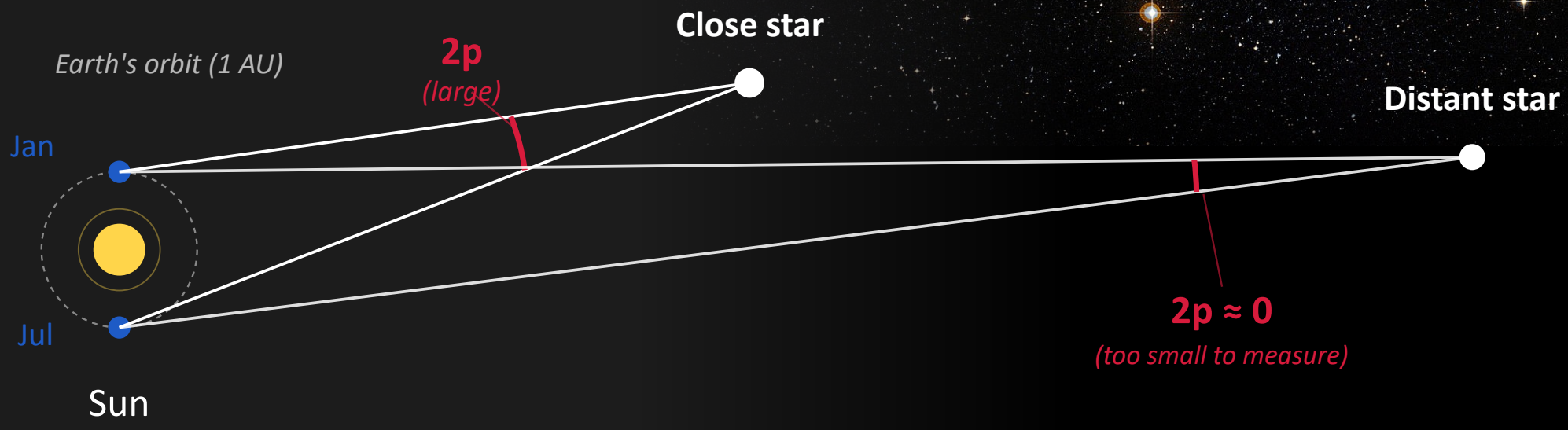
Gaia DR3 based res.



E. Putney, D. Shih, **SHL**, and M. R. Buckley, arXiv:2512.09989.
also in workshop paper at NeurIPS 2025 ML4PS workshop

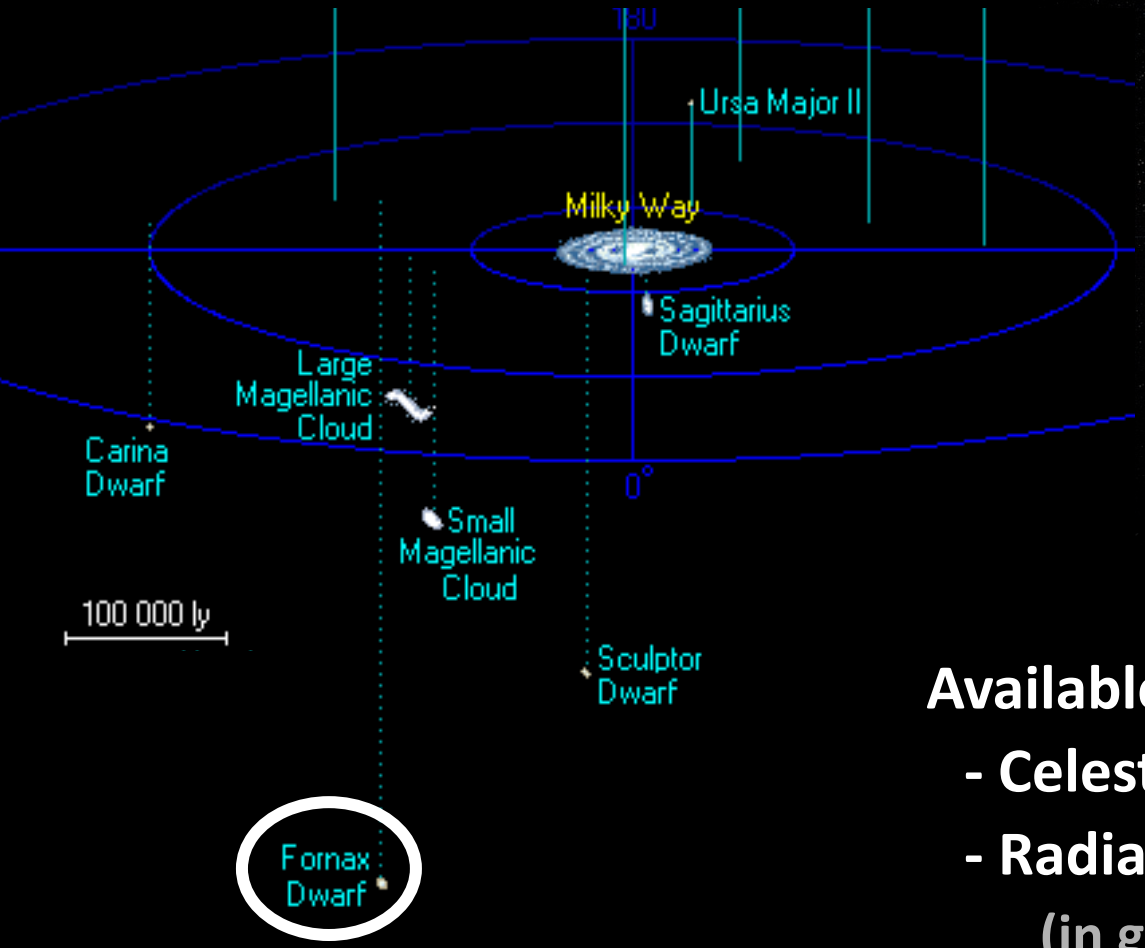
Is the same technique applicable to other galaxies?

- ✓ Yes, if full 6D information is available.
- ✗ No, many surveys for distant galaxies provides only limited information.



Example:
Dwarf Spheroidal Galaxies

Round faint satellite galaxies orbiting the Milky Way.



Fornax Dwarf
Digitized Sky Survey 2

Available info. for member stars

- **Celestial position on the sky (x, y)**
- **Radial velocity (v_z)**
  (in galactocentric coordinate of dSph.)

http://www.atlasoftheuniverse.com/sattelit.html

But,
we need a full 6D phase space density.

Can we recover those from 3D info?

But,
we need a full 6D phase space density.

Can we recover those from 3D info?

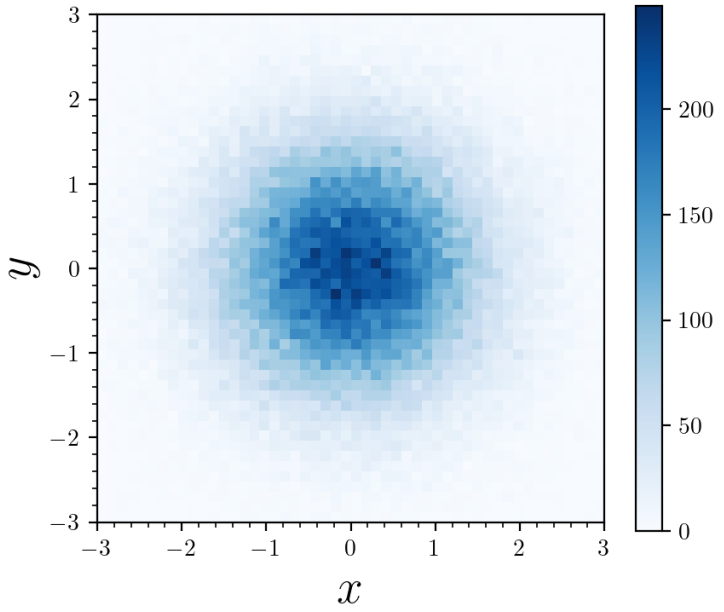
Yes, we can impose
symmetry and physics constraints.

Equivariant Continuous Normalizing Flows

Continuous Normalizing Flows (CNFs) are NFs learning infinitesimal coordinate transformation.

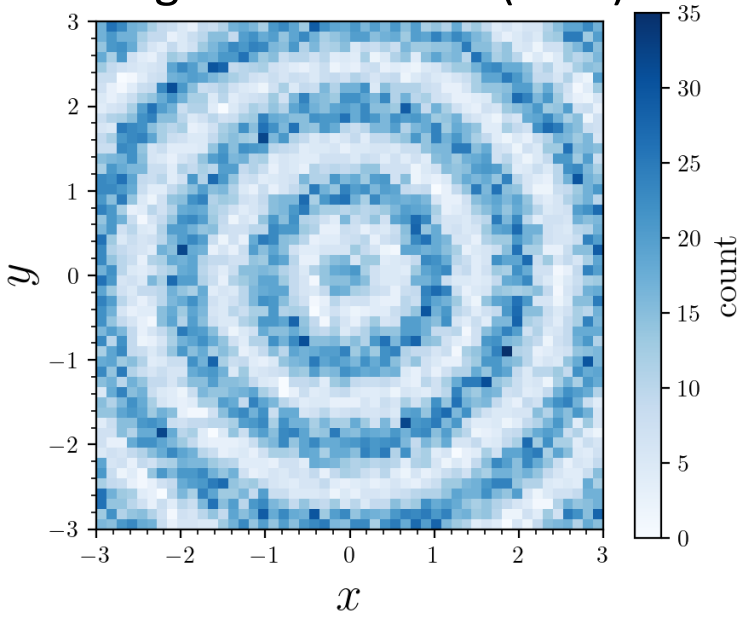
$$\frac{d\vec{x}}{dt} = \vec{G}(\vec{x}, t) \longrightarrow \frac{d\vec{x}}{dt} = \hat{r}g(\vec{x}, t)$$

Base distribution (known)



Equiv. CNF

Target distribution (data)



Conditions:

- **Base distribution** is **invariant**: spherically symmetric Gaussian
- **Transformation** is **equivariant**: transformation is confined to radial direction

Equivariant CNFs: cored profile

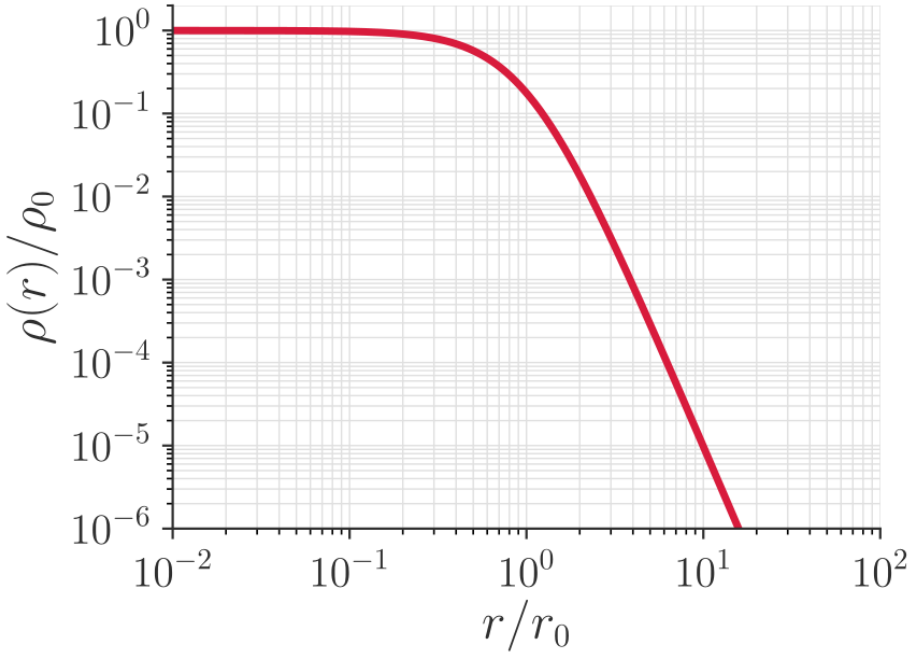
CNFs can be further constrained to model only **cored** density profile.

$$\frac{d\vec{x}}{dt} = \hat{r} g(\vec{x}, t) \longrightarrow \frac{d\vec{x}}{dt} = \hat{r} \tanh\left[\frac{|\vec{x}|}{r_0}\right] g(\vec{x}, t)$$

Mechanism:
- Base Gaussian distribution is already cored at origin.
- Suppressed flow at the origin → Flat core remains flat.

Example: Plummer profile

$$\rho(r) = \rho_0 \left[1 + \frac{r^2}{r_0^2}\right]^{-\frac{5}{2}}$$



Equivariant CNFs: cuspy profile

The **cored** density model can be expanded to cover **cuspy** densities

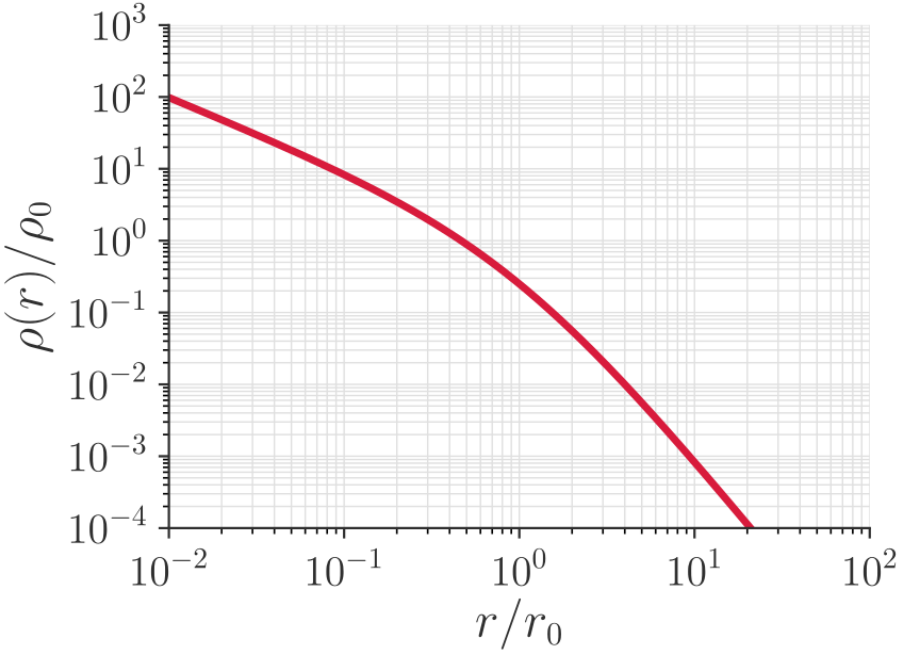
$$|r| \rightarrow |r|^{c+1} \longrightarrow \text{Jacobian} \propto r^{-\frac{3c}{1+c}}$$

(applied to cored density model)

Mechanism:
- Power law transform turns cored density models to cuspy density models.

Example: NFW profile

$$\rho(r) = \rho_0 \left[\frac{r}{r_0}\right]^{-1} \left[1 + \frac{r}{r_0}\right]^{-2}$$



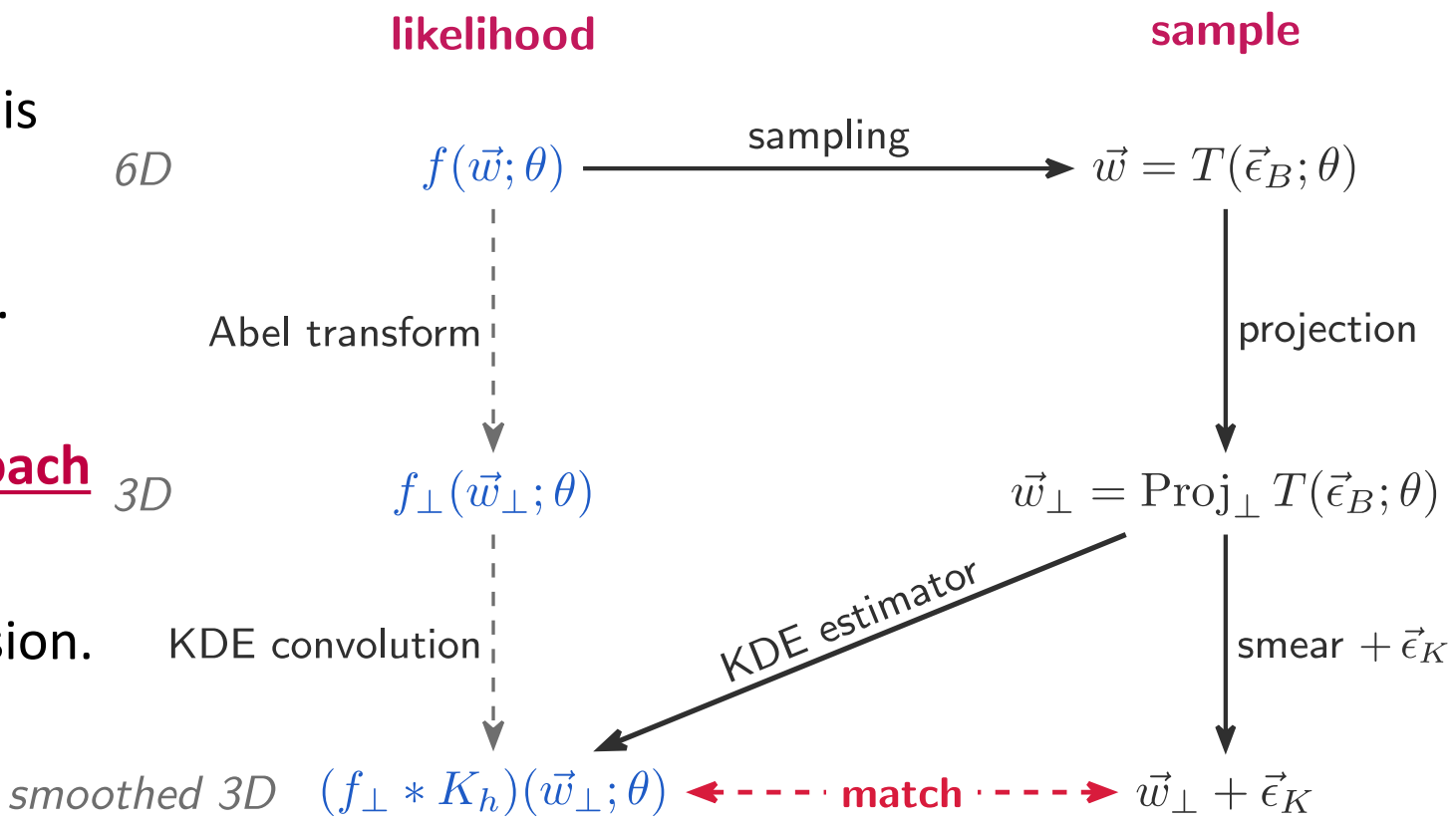
JFlow Loss Function Construction

Obstacle:

- Our likelihood model is **6D** phase space density model.
- Data has only **3D** info.

Solution:

- Use **generative approach** to perform MLE at a space with **matched** dimension.



dashed grey: analytic but intractable.
solid: computable from CNF samples.
dashed red: the equality we optimize.

JFlow Loss Function

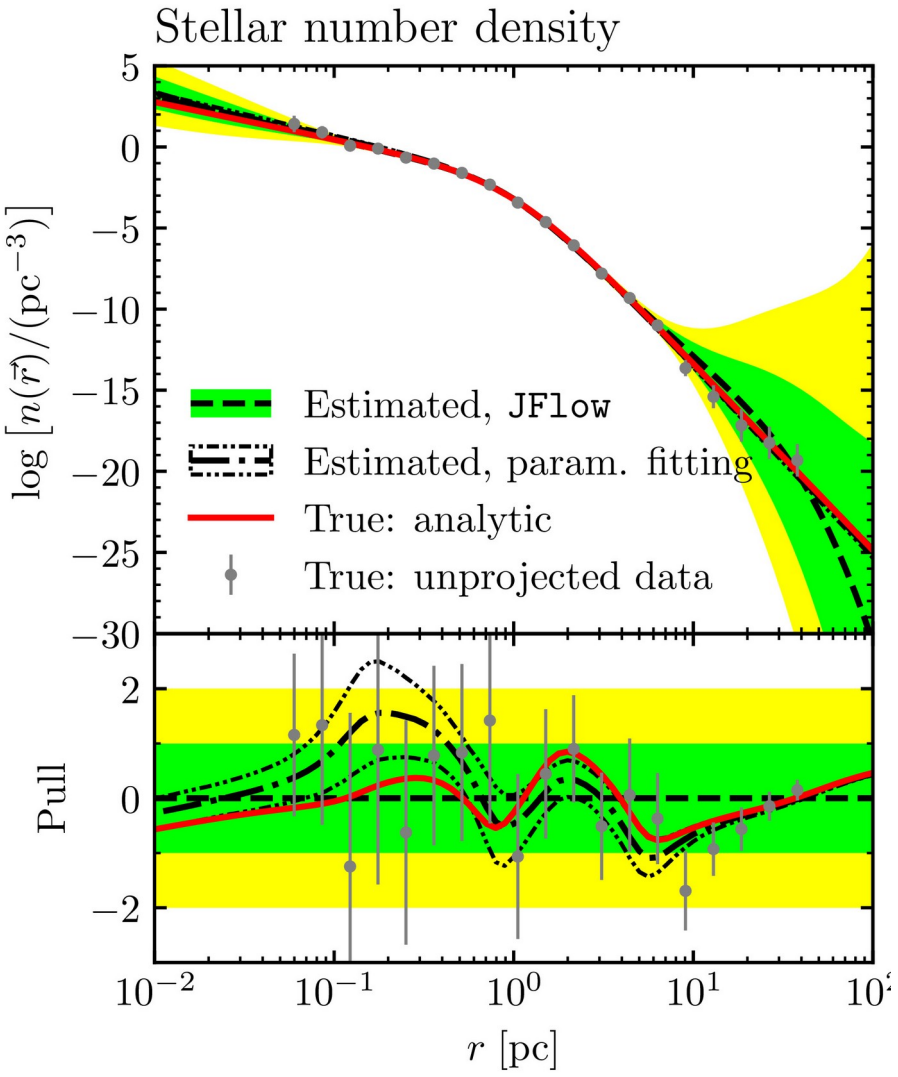
The JFlow algorithm trains 6D likelihood model by minimizing **KL divergence** at smoothed 3D space.

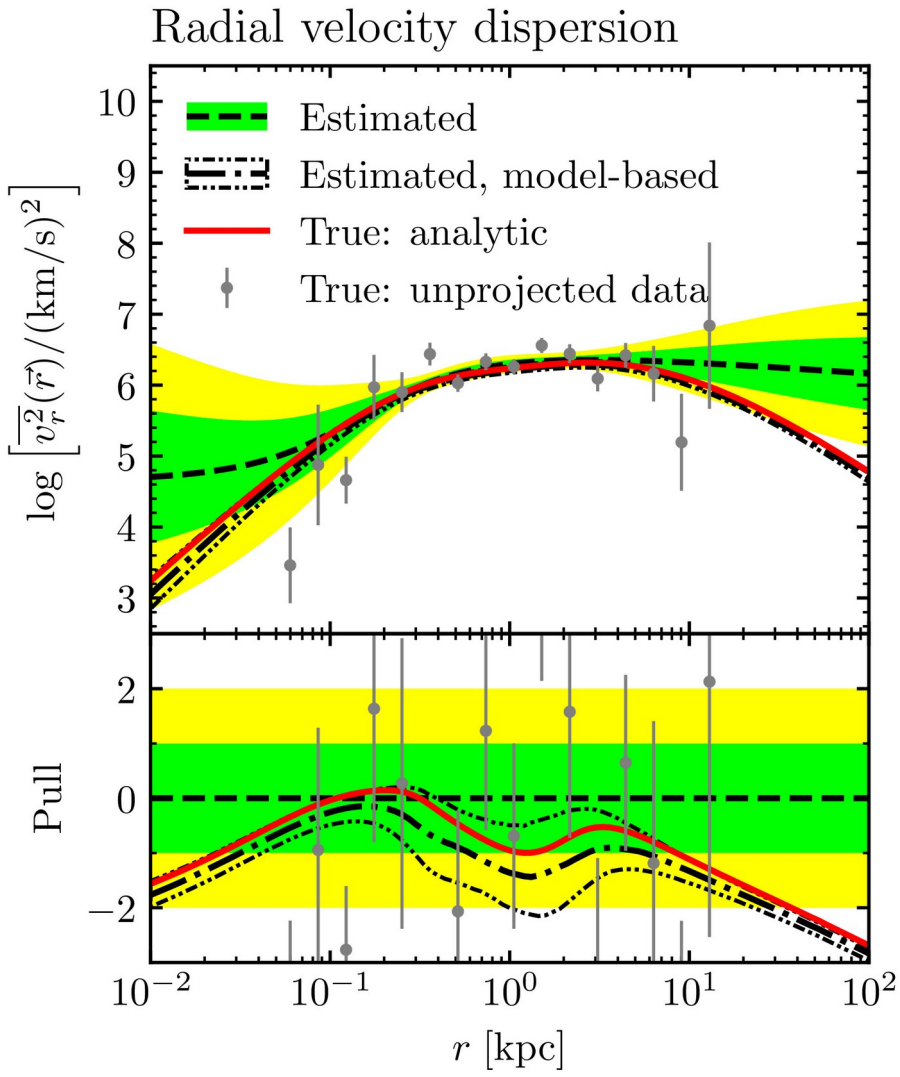
$$\mathcal{L}(\theta) = \int d\vec{w}_\perp \; p * K_h(\vec{w}_\perp) \; \log \hat{p} * K_h(\vec{w}_\perp; \theta)$$

Resulting JFlow training objective:

$$\mathcal{L}(\theta) = \frac{1}{N N_K} \sum_{a=1}^{N} \sum_{b=1}^{N_K} \log \frac{1}{N_G} \sum_{c=1}^{N_G} K_h \left[\vec{w}_\perp^{(a)} + \vec{\epsilon}^{(b)} - \vec{T}(\vec{z}^{(c)}; \theta) \right]$$

Results: stellar number density & radial velocity dispersion





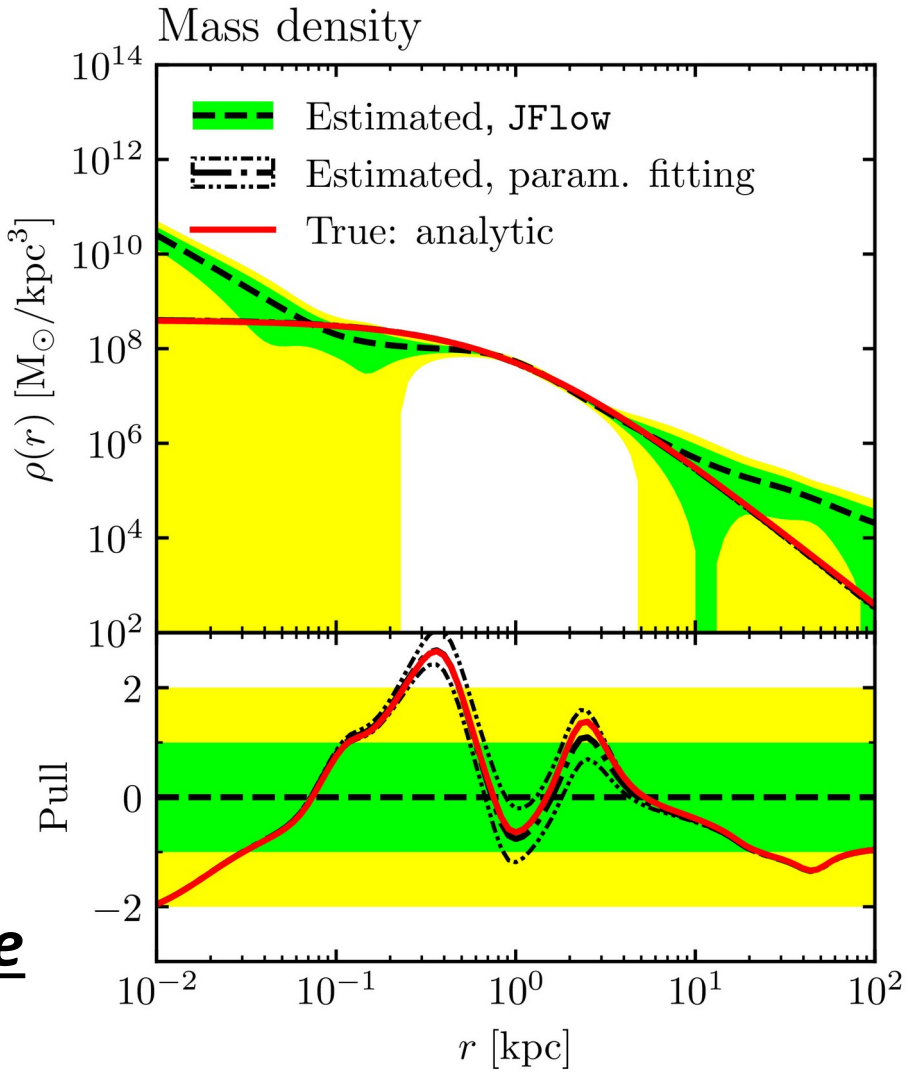
Results: dark matter mass density

Dataset

- Simulated spherical galaxy
- Cored dark matter density profile (known)
- 10K samples
- See Gaia Challenge repository

  astrowiki.surrey.ac.uk

JFlow successfully recovers the *true dark matter density profile* from *limited information*.

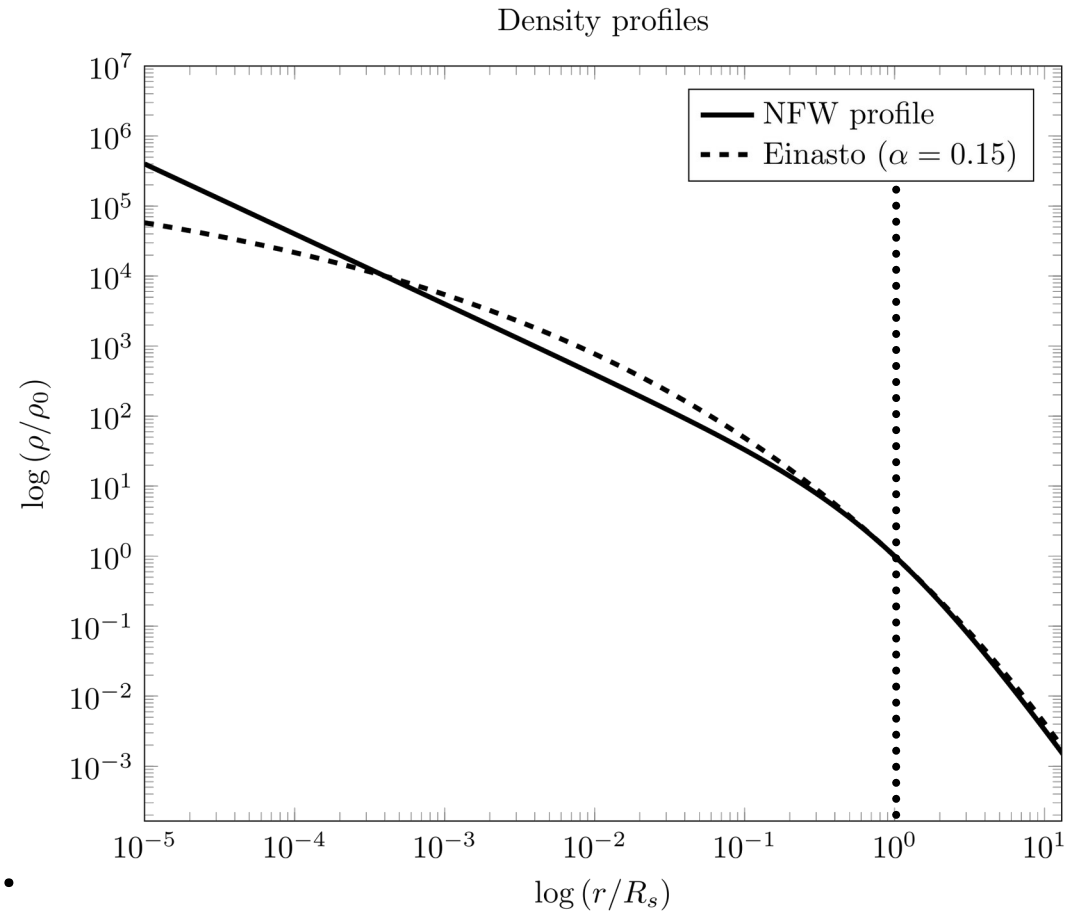


What physics can we study with these ML methods?

Navarro–Frenk–White (NFW) profile

A commonly used dark matter halo model empirically identified in N-body simulations

$$\rho(r) = \frac{\rho_0}{\frac{r}{R_s}\left(1+\frac{r}{R_s}\right)^2}$$



If dark matter exhibits non-trivial interactions, the **halo shape may vary**.

Self-interacting dark matter, wave dark matter ….

https://en.wikipedia.org/wiki/Navarro%E2%80%93Frenk%E2%80%93White_profile

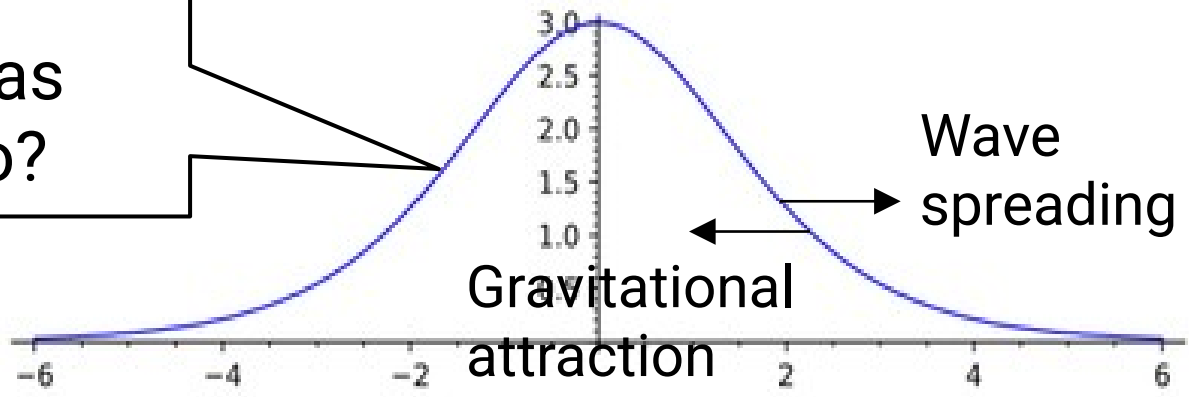
Example: Wave Dark Matter

If DM mass is so light (e.g. very light axions) so that

inter-particle spacing << de Broglie wavelength

DM exhibits **wave-like** behavior.

Nontrivial stable solution:
Soliton
→ Soliton solution as
a dark matter halo?



Smoking gun signatures

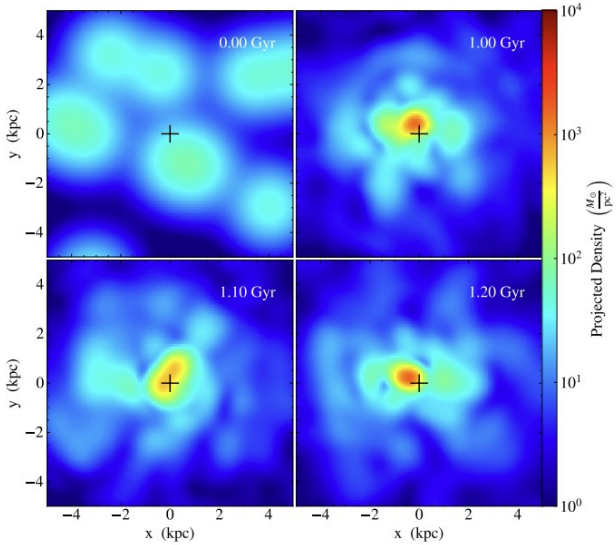
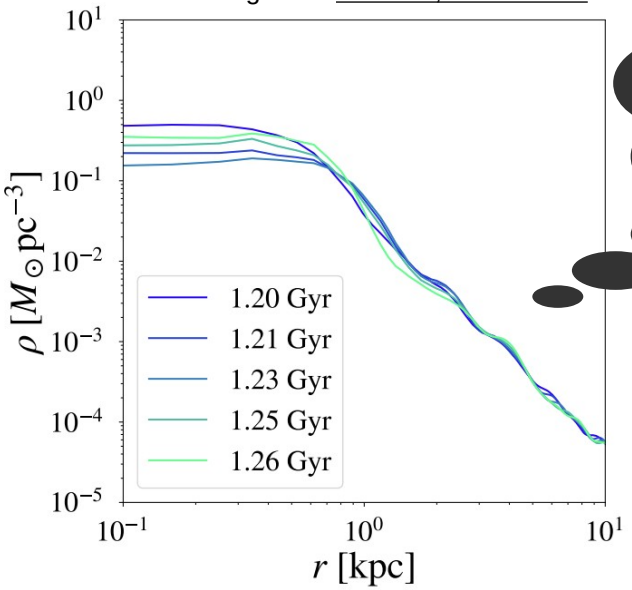


Fig. from Lam Hui, 2101.11735



Soliton Oscillations

Soliton Core

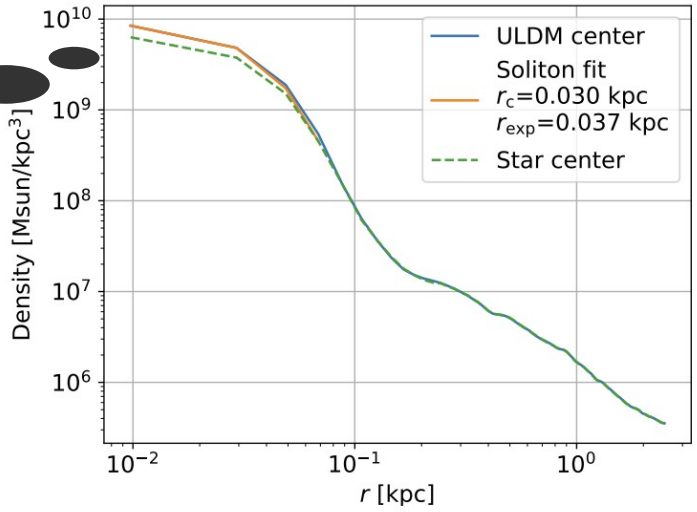
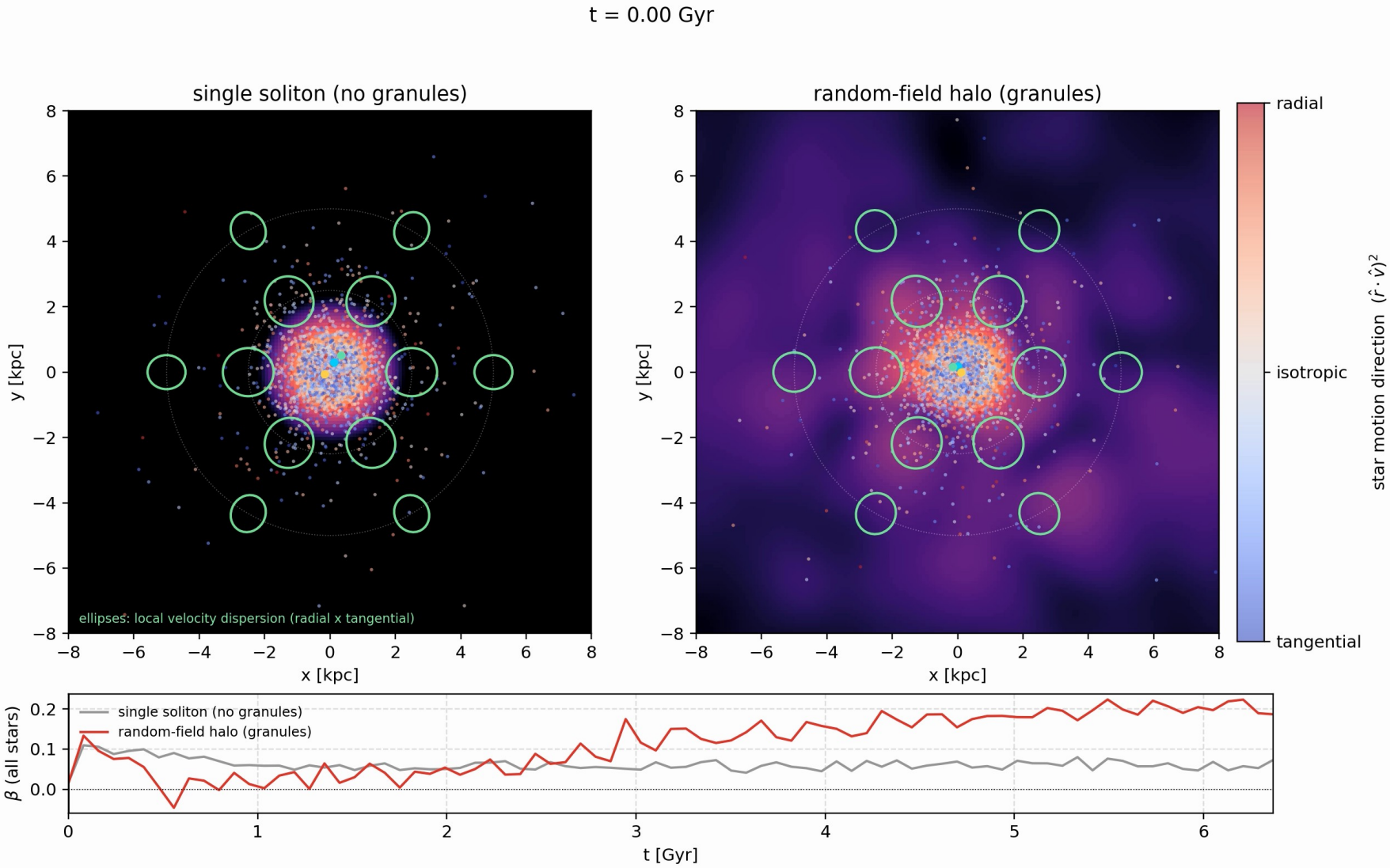


Fig. from talk by Teodori Luca, IBS Let there be light (particles) Workshop

Altered stellar kinematics



Yeji Park, SHL, work in progress.

gaia

GAIA DATA RELEASE 4 (GAIA DR4)

The original Gaia DR4 data will become available from the Gaia ESA Archive. The expected content of Gaia DR4, pending certain processing and validation activities, is described here and summarised in this table.

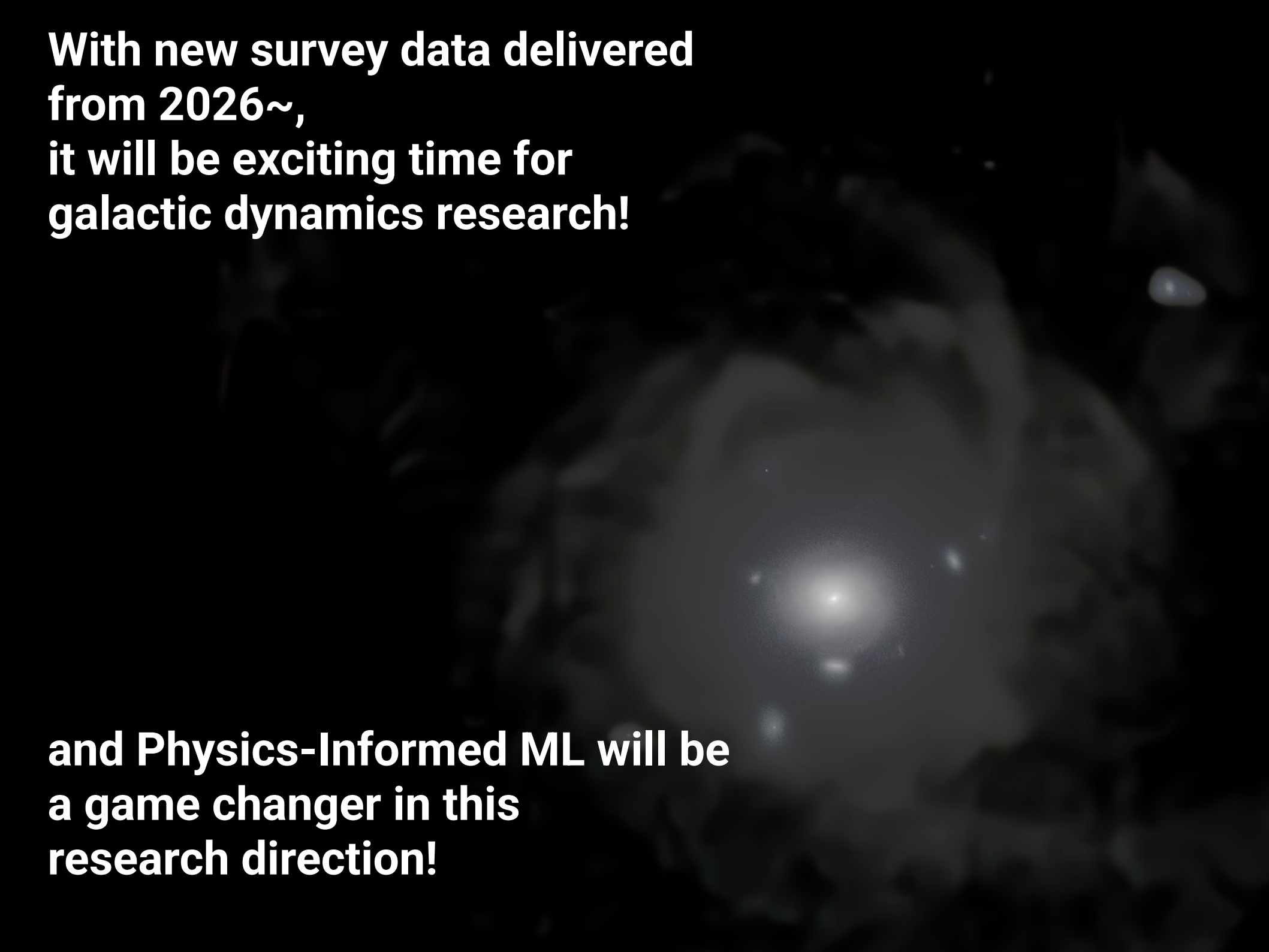


Current: Gaia DR3
1.5 billion sources

Future: Gaia DR4
2.8 billion sources

×2 in stat.

*** Gaia DR3: Full 6D phase space for 33M sources.**


With new survey data delivered
from 2026~,
it will be exciting time for
galactic dynamics research!
and Physics-Informed ML will be
a game changer in this
research direction!

Awesome collaborators of my projects:



Prof. David Shih
(Rutgers)



Prof. Matthew Buckley
(Rutgers)



Prof. Mihoko Nojiri
(KEK)



Prof. Kohei Hayashi
(NIT, Sendai College)



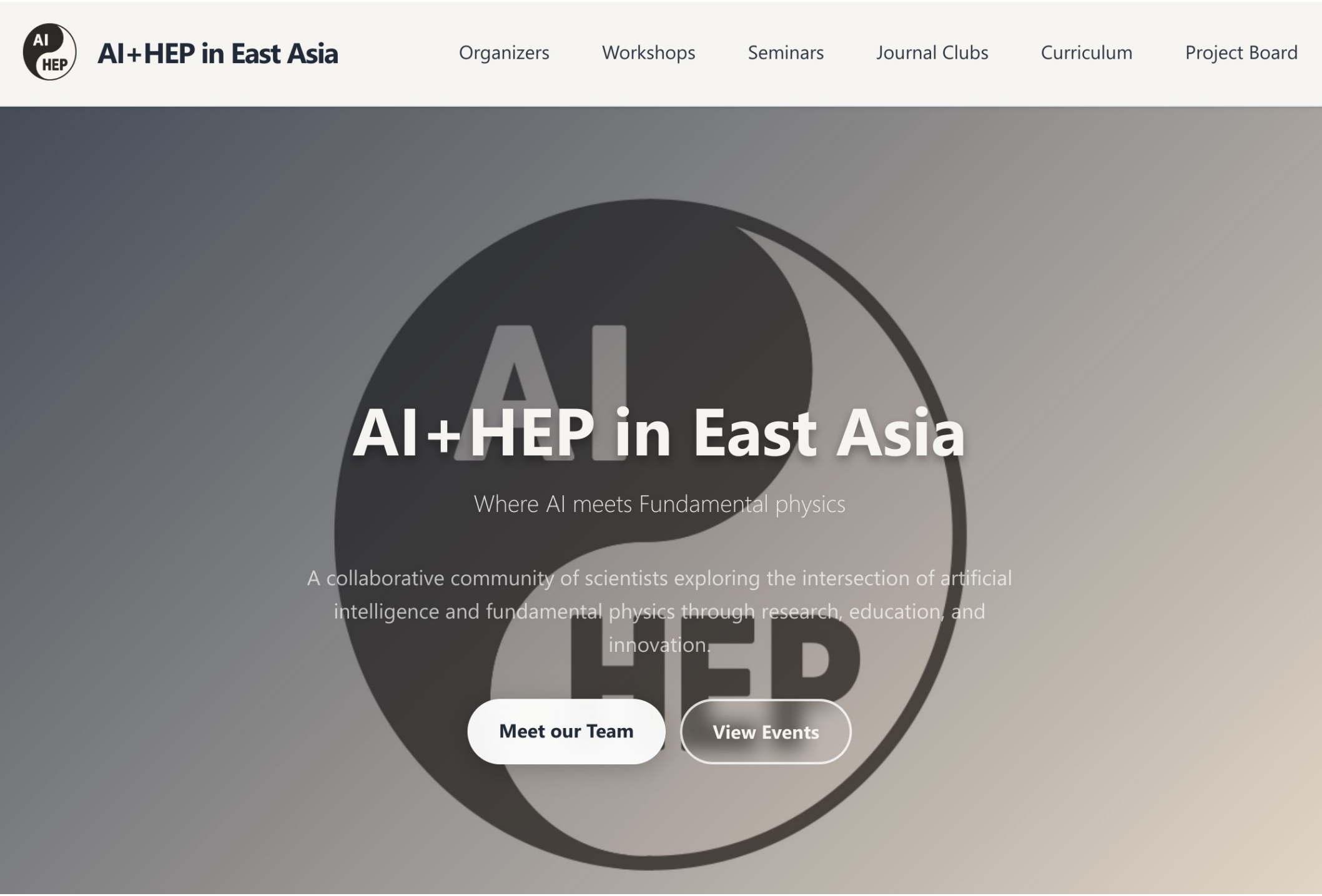
Dr. Eric Putney
(Postdoc at Rutgers)



Prof. Shigeki Matsumoto
(IPMU)



Dr. Shunichi Horigome
(Tohoku)



URL: http://ai-hep.github.io

AI+HEP in East Asia

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ASSOCIATE PROFESSOR

Kobayashi-Maskawa Institute

AI FOR SCIENCE

Vinicius Mikuni is an Associate Professor using AI for scientific discovery at the KMI Institute. He earned his PhD in 2021 from the University of Zurich, and worked as a Postdoctoral Fellow at



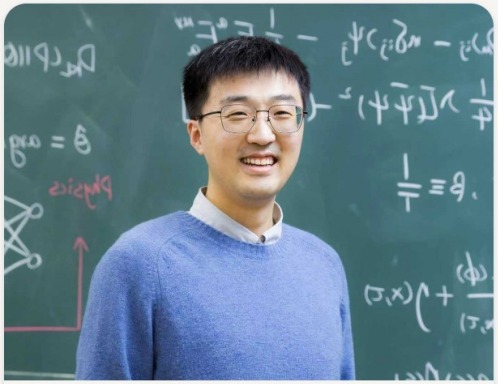
Huilin Qu

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Tsung-Dao Lee Institute, Shanghai Jiao Tong University

REPRESENTATION LEARNING · FOUNDATION MODEL · COLLIDER & JET PHYSICS · DARK MATTER AND NEUTRINO EXPERIMENTS

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Lingxiao Wang

DEPUTY DIRECTOR OF AI AS SCIENCE TEAM

RIKEN Center for Interdisciplinary Theoretical and Mathematical Sciences (iTHEMS) / Institute for Physics of Intelligence, University of Tokyo

MACHINE LEARNING IN PHYSICS · QUANTUM CHROMODYNAMICS · LATTICE FIELD THEORY · AI FOR SCIENCE

Workshops



AI+HEP Workshop 2026

Dates: Jan 19–23, 2026

Location: KEK, Tsukuba, Japan

Event Page



AI+HEP Workshop 2025

Dates: Feb 23–28, 2025

Location: IBS (Institute for Basic Science), Daejeon, Korea

Event Page

https://ai-hep.github.io/



ML4Jets 2027 at Nagoya







Thank you
for listening.

Backups

Physics-Informed Machine Learning

Input-level

- Physics-Informed inputs for jet tagging
- ...

Architecture-level

- Equivariant jet taggers
- JFlow – neural model of dwarf spheroidal galaxies
- ...

Loss function-level

- NNPDF
- CBE solver for dark matter density estimations
- ...

Single Framework, Multiple Systems

NF + PINN

Milky Way

Gaia DR3, 6D phase space

$f(x, v)$

Normalizing Flows

$a(x)$

PINN with CBE

Results:

DM density in solar neighborhood, and stellar halo

2205.01129
2211.11765
2305.13358

SHL, Putney, Buckley, Shih

PINN + Dust Correction

Milky Way

Gaia DR3, 6D phase space

$f(x, v)$

Normalizing Flows

$a(x)$

PINN with CBE
+ selection efficiency modeling

Results:

DM density on the stellar disk

2412.14236
2512.09989

Putney, Shih, Buckley, SHL

GalaxyScore

Milky Way

6D phase space

$f(x, v)$

Score matching

$a(x)$

PINN with CBE

Results:

Faster inference model

ML4PS @ NeurIPS 2025

SHL, Shih, Buckley, Putney

JFlow

Dwarf Spheroidals

3D subspace

$f(x, v)$

Equivariant CNF
+ phys. constraints

$a(x)$

Solve Jeans Equations

Results:

DM density estimation from limited info.

2505.00763

SHL, Hayashi, Horigome, Matsumoto, Nojiri

Two Ways to Solve for a(x)

$$\mathcal{L}(a(x)) = \mathbf{E}_x \, \mathbf{E}_{v|x} \left[\vec{v} \cdot \frac{\partial f}{\partial \vec{x}} + \vec{a} \cdot \frac{\partial f}{\partial \vec{v}} \right]^2$$

Solve for the potential:

Green et. al. (arXiv: 2011.04673, 2205.02244)

Parametrize potential with a NN:

$$\Phi(x) = \mathrm{NN}(x;\theta)$$
$$a(x) = -\nabla\Phi(x)$$

✓ **Strictly conservative**
by construction

✗ **Training derivatives of NN**
may have minor quality issue

Solve for the acceleration:

An et. al. (arXiv: 2106.05981)
Naik et. al. (arXiv: 2112.07657)

Parametrize acceleration with a NN or directly solve

$$a(x) = \mathrm{NN}(x;\theta)$$

✓ **Analytic solution exists**
PINN training is optional

✗ **Not necessarily conservative**

How did we measure DM density so far?

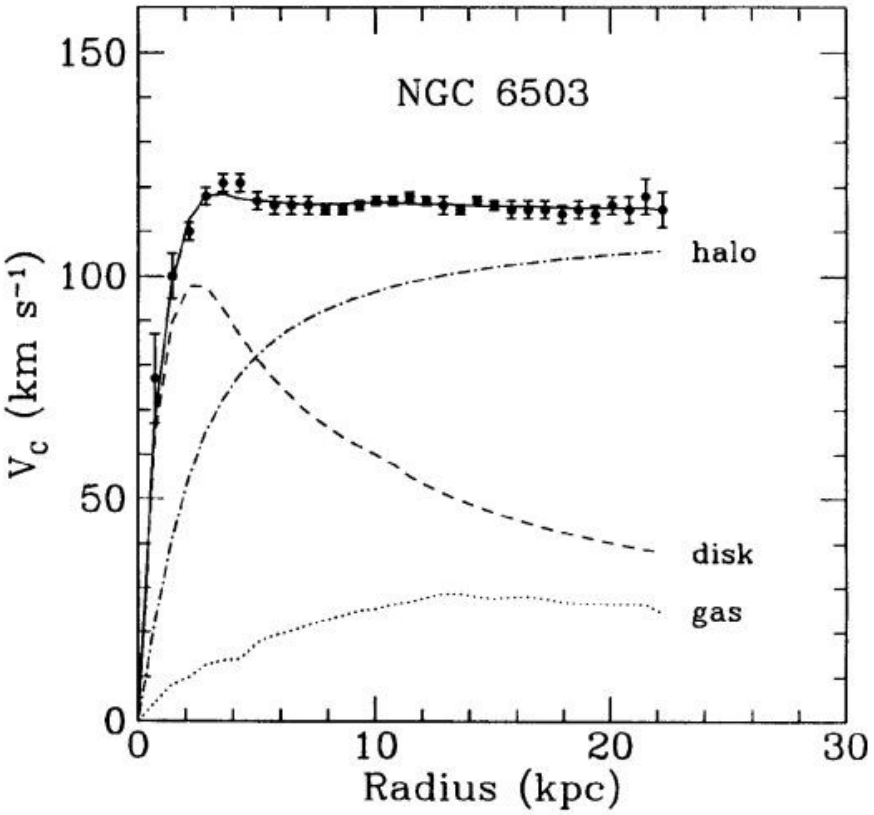
Enclosed Mass and Orbital Speed

The stars orbit faster if there is more enclosed mass.

→ If stars orbiting faster than expected, invisible mass exists — *dark matter.*

How did we measure DM density so far?

The historical method: galaxy rotation curve



Galaxy rotation curve of NGC 6503
Freese (arXiv:0812.4005)

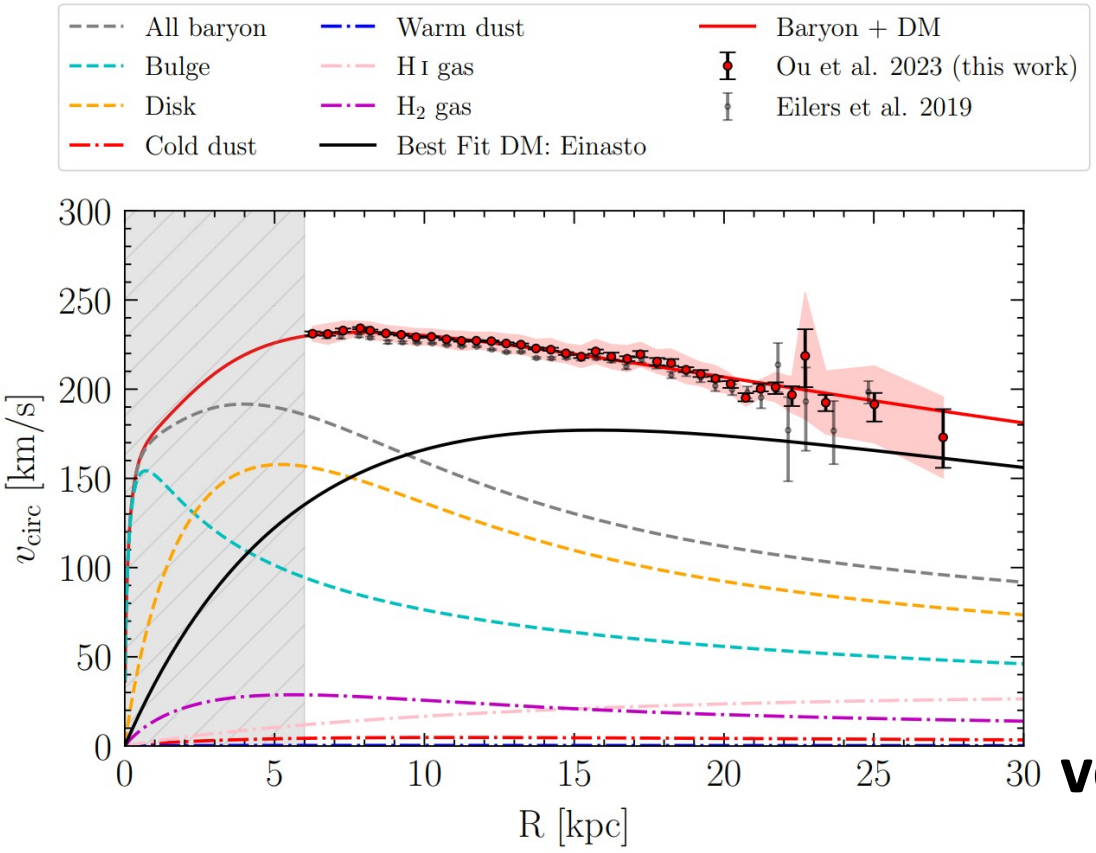
1. **measure orbital speed of stars at given radius, $v_c(R)$.**
2. **compute expected orbital speed of stars given baryon and gas densities,**

$$v_{\rm circ}^2(R) = \frac{GM(R)}{R}.$$

3. **the difference can be interpreted as the contribution from the dark matter.**

The rotation curve served as the first evidence of *dark matter.*

Galaxy Rotation Curve of the Milky Way



Galaxy rotation curve of the Milky Way
Ou, Eliers, Necib, and Frebel (arXiv:2303.12838)

	Einasto
Normalization Mass (M_0)	$0.62^{+0.12}_{-0.11} \times 10^{11}\ M_\odot$
Scale Radius (r_s)	$3.86^{+0.35}_{-0.38}$ kpc
Slope Parameter (α, β)	$0.91^{+0.04}_{-0.05}$
Virial Mass (M_{200})	$1.81^{+0.06}_{-0.05} \times 10^{11}\ M_\odot$
Virial Radius (r_{200})	$119.35^{+1.37}_{-1.21}$ kpc
Concentration (c_{200})	$13.02^{+0.11}_{-0.10}$
Local Dark Matter Density ($\rho_{\rm DM,\odot}$)	$0.447^{+0.004}_{-0.004}$ GeV cm^{-3}
***J*-factor** ($J(\theta < 15°)$)	$15.8^{+1.08}_{-0.93} \times 10^{22}$ GeV^2 cm^{-5}
χ^2 **per d.o.f.** (χ^2_ν)	2.97

[a] Fitted in logarithmic scale.

The rotation curves provide very *high-precision measurement* of the DM density,

but with *limitations*...

Limitations of Galaxy Rotation Curve

The main limitations of galaxy rotation curve is that it is only sensitive to a summary statistics: *enclosed mass*.

$$v_{\rm circ}^2(R) = \frac{GM(R)}{R}.$$

Therefore, this is not a local DM density measurement.

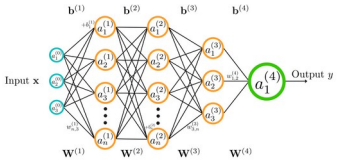
→ How do we measure local DM density then?

Physics-Informed Machine Learning?

Physics-Informed Machine Learning **is**
a class of machine learning methods incorporating with physics knowledge.

Data Inputs
what we measuring ---
event records, images,
astronomical surveys,

Neural networks



Physics
Domain-specific knowledge ---
theory, symmetry, differential equations, conservation laws, constraints

Physics-Informed Models

Why make physics built-in?

Data-driven
Fully using information in dataset

Consistent
Making predictions consistent with physics

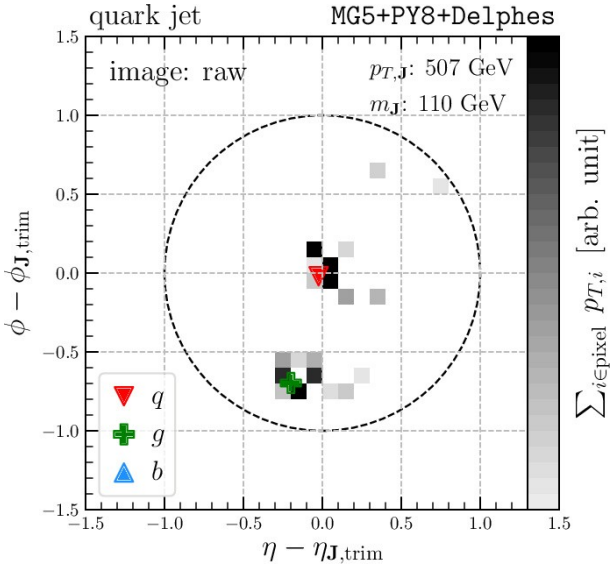
Transparent
Interpretable in terms of injected physics

Equivariant Jet Taggers for Colliders --- Physics-Informed Architectures

Neural networks have been used for identifying the origin of jets.

- Convolutional NN (1511.05190)
- Graph NN
- Transformer (2202.03772)

Current state-of-the-art jet taggers includes **equivariant models**:



Best jet tagging models!

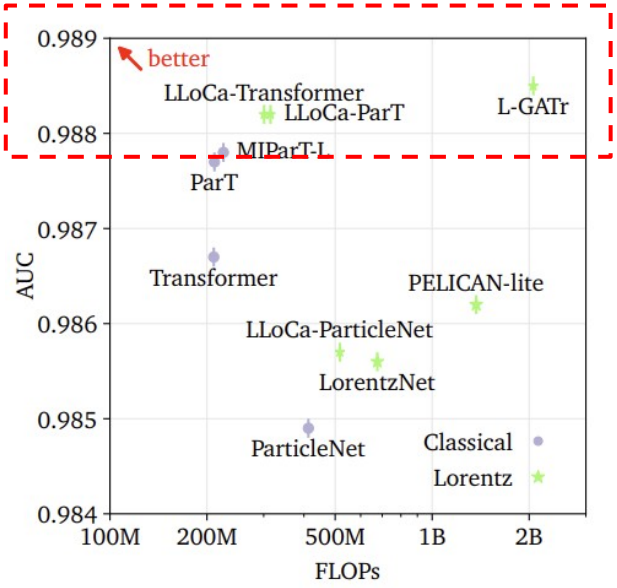


Fig from Luigi et. al., 2508.14898

Lorentz Symmetry

- **LorentzNet (Gong et. al., arXiv:2201.08187)**
- **L-Gatr (Spinner et. al., arxiv:2405.14806)**
- **...**

Permutation Symmetry

- **PELICAN (Bogatskiy et. al., arXiv:2307.16506)**
- **...**

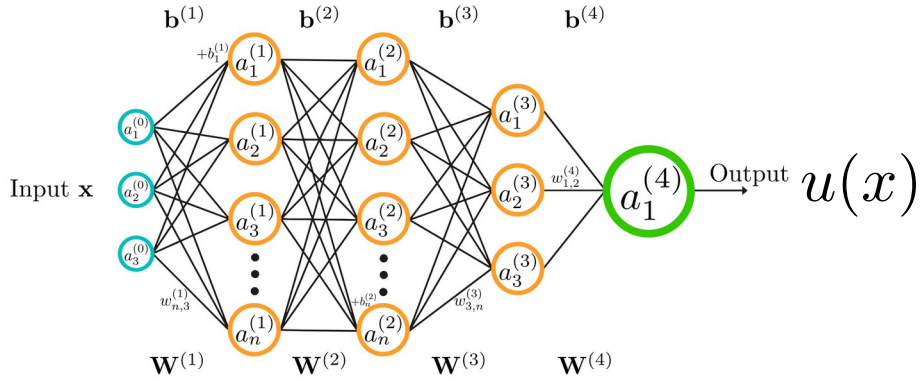
Physics-Informed Neural Network

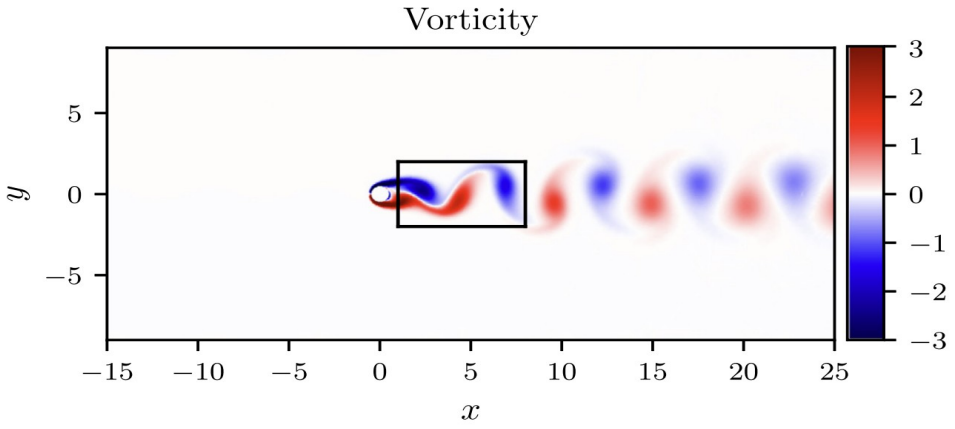
Neural Network Learning PDE Solutions

Raissi et. al. (arXiv:1711.10561, 1711.10566)

PINN **is a neural network modeling solution of differential equations, simply minimizing the residuals.**

Neural network as solution model





Data loss

$$\mathcal{L}_{\text{Data}}(u) = \mathbf{E}\,|u - u_{\text{true}}|^2$$

PDE residual loss

$$\mathcal{L}_{\text{PDE}}(u) = \mathbf{E}\,|\text{PDE}(u)|^2$$

Boundary condition loss

$$\mathcal{L}_{\text{BC}}(u) = \mathbf{E}\,|\text{BC}(u)|^2$$

Minimize

PDE solution